A

Project Thesis

On

TWO TANK LEVEL CONTROL SYSTEMS USING DYNAMIC MATRIX CONTROL AND STUDY OF ITS TUNING PARAMETER

Submitted

in partial fulfilment of requirement for the award of degree

of

Master of Technology

in

Electronics & Communication Engineering
(Electronics & Instrumentation Engineering)

By

UDIPT WAMHNE
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DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY
ROURKELA- 769008

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Under the supervision of

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Dedicated

to

My beloved Parents

NATIONAL INSTITUTE OF TECHNOLOGY
ROURKELA

CERTIFICATE

This is to certify that the thesis report entitled "**Two Tank level control systems using Dynamic Matrix Control and study of its tuning parameter**" submitted by **Mr. Udipt Wamhne** in the partial fulfilment of the requirements of the award of Master of Technology in **Electronics and Communication Engineering** with the specialization in "**Electronics and Instrumentation**" during session 2013-2015 at **National Institute of Technology, Rourkela** is an authentic work by him under my supervision and guidance.

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Dept. of Electronics and Communication Engineering
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Date:
Place: Rourkela

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Udipt Wamhne

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CONTENTS

ABSTRACT

Liquid level has a major role in the process industries especially in chemical plants, pharmaceutical industries, etc and the controlling of this parameter is a big task. Every time controlling manually is not possible therefore by using simulation methods, these targets are achieved. This project deals with the Two Tank Systems on which Dynamic Matrix Controller algorithm has been applied for the simulation work. Effect of tuning parameters such as prediction horizon (p), control horizon (m) and model length (n) are studied and data were collected. Different performances i.e. rise time, settling time etc. were seen for different varying tuning parameters. Also the Empirical Formula has been derived, based on the observations for optimal performance of the system. Process parameters have been changed and best performance has been observed with respect to the time constant. This project work manages the study and examination of DMC for the given Tank System under MATLAB simulation window.

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Chapter – 1
Introduction

INTRODUCTION

In this chapter, the overview and objective of the project is been discussed. A brief writing about the controlling method used is also given.

1.1 Overview

Liquid level control shows wide applications in Industrial Process, as in industrial chemical and spray coating, pharmaceutical industries, nuclear power generation plant, filtration, effluent treatment, water purification systems etc. typical actuators used in liquid control systems include motorized valves, pumps, on-off valves, etc. In addition, level sensors such as capacitance probe, displacement float, pressure sensor, etc., provide liquid level measurement for the reason of feedback control [1].

Dynamic Matrix Control is a sort of control figuring in which present control movement is obtained by settling a restricted horizon of open loop perfect control issue using the present state of the plant as the beginning state of the plant. This strategy is again and again achieved for each testing point. The optimization yields a perfect control progression and the first control in this group is associated with the plant. [2].

This project describes the laboratory process, which was designed to illustrate performance limitations due to zero location in the multivariable control systems. This procedure is called four-tank process and comprises of four interconnected water tanks and two pumps. Its inputs are the voltages to the two pumps and the output are the water levels in the down two tanks. The four-tank procedure can without much of a stretch be manufacture by utilizing two, two tank systems interconnected with each other [3].

1.2 Objective

The main objective of the project is to maintain the level of the tank upto desired level set point using Dynamic Matrix Controlling method and analysis of different tuning parameters on the system process for different time constants and finally deriving a generalized empirical relationship of these tuning parameters with respect to the time constant.

1.3 MATLAB

MATLAB is a programming language for specialized processing which coordinates processing, visualization, and programming in a simple to-utilize environment where issues and arrangements are communicated in natural numerical documentation. Ordinary uses include: Math and calculation. In this project, MATLAB version R2011a is used for simulations [10].

1.4 DMC Working

The main purpose of Mode Predictive Control is to determine the inputs that best suits to a given performance conditions. It predicts about the system behavior if the given input signal is applied. This calculation utilizes the samples of step response of plant to catch plant's temperament and tackles a control issue for an ideal control activity to track the given input. Following approximation is used for plant response [2]:

$$\begin{aligned} Y(k) &= \sum_{i=1}^{\infty} S_i \Delta u_{k-i} \\ &= S_1 \Delta u_{k-1} + S_2 \Delta u_{k-2} + \cdots + S_N \Delta u_{k-N} \end{aligned}$$

It works according to following steps:

1. Determine Step Response Coefficient Matrix

   S = $[S_1, S_2, S_3, \dots., S_n]$
2. Find S_f and S_p matrix from S.
3. Declare W1 and W2 matrix and calculate feedback gain Matrix:

   K = $(S_f^T W1^T W1 S_f + \ W2^T W2)^{-1} S_f^T W1^T W1$
4. Evaluate error E = r – y_free.
5. Now determine the required change in control weight at instant k:

   $\Delta u_f(k)$ = K*E and update value of controller output:

   u(k+1) = u initial + $\Delta u_f(k)$
6. Get plant response at instant k+1:

   y(k+1) with respect to u(k+1) and set point value r.
7. Predict the future response of plant:

   Ymod(k+1) = S(1)* $\Delta u_p(k)$ + Sp*$\Delta u_p{}'$ + S(N)*u(k-n+1)

8. Now update this value as new value of y_free.

Now, repeat steps 4 to step 7 for each time sample.

1.5 Previous MPC Application

The utilization of MPC calculation extends back to mid 1970's. The principle model prescient control calculation was Model Predictive Heuristic Control (MPHC), Richalet et al (Richalet 1978) in 1976. In 1979, Cutler and Ramaker exhibited their adaptation called Dynamic Matrix Control (DMC) [5], where control yields are processed applying purported subsiding skyline rule. The time horizon was quickened one stage ahead during every control cycle and the optimization issue was seen more than once during every control cycle. An interesting feature of these predictive calculations is their ability to make do with unequivocal limitations on system variables. Goals are released in most of other control calculations.

1.6 Various types of MPC

- Feedback MPC: It mitigates shrinkage of practical area.
- Robust MPC: It gives ensured possibility and steadiness of the procedure on which it is connected.
- Decentralized MPC: It gives quick reaction. Mostly this is utilized as a part of computerization procedure.
- Pre-computed MPC: It is a disconnected from the net advancement process. Parameters are illuminated utilizing direct or quadratic programming.

Chapter – 2

Literature Survey

LITERATURE SURVEY

Some research articles are referred and studied without whose this project could not be initiated. This chapter includes the journals and books adopted for completing the work.

- H. Pan, H. Wong, V. Kapila and M. S. Queiroz, "Experimental validation of a nonlinear backstepping liquid level controller for a state coupled two tank system," Control Engineering Practice 13, Elsevier,2005, pp. 27–40

  This paper gives the nonlinear control plan issue for a state-coupled, two-tank fluid level system. It was persuaded by wanting to give exact fluid level control, an arrangement of nonlinear back-stepping systems is created for the state-coupled, two-tank fluid level system flow. In particular, a model based back-stepping controller and a versatile back-stepping controller are intended for the two-tank fluid level system. Some applications are given which uses liquid level control as the output.

- B. Wayne Bequette, Process Control: Modeling, Design and Simulation, Pearson Education Inc., USA, 2003

  This book is the complete prologue to process control that completely coordinates programming apparatuses helping you ace basic procedures hands-on, utilizing MATLAB-based PC simulations. Basic knowledge of Dynamic Matrix Controller was obtained with an MATLAB programming examples.

- K. H. Johansson, "The Quadruple Tank Process – A Multivariable Laboratory Process with an Adjustable Zero," IEEE Transactions on Control Systems Technology, vol. 8, no. 3, May 2000

  This Journal gives a brief introduction to four interconnected water tanks systems. The linearized progress of the system having a multivariable zero that is conceivable to move along the genuine pivot by changing a valve is also discussed. Exact models are given for both physical and test information and decentralized control is also shown in the methodology.

- S. Bhanot, "Process Control, Principle and Applications," Oxford University Press

  This book describes the mathematical modeling method which is used to obtained the final transfer function of the tank system used for experimental works. Also relations of interacting and non-interacting tanks are also described in detail.

- S. N. Maiti and D. N. Saraf, " Adaptive Dynamic Matrix Control of a Distillation Column with closed loop online identification," J. Proc. Cont., Elsevier, vol. 5, no. 5, pp. 315-327, 1995

  This paper displays dynamic system control which uses a large number of step response coefficients in the model. Recursive identification of these coefficients at each sampling instant are shown impractical.

- J. M. Lopez, G. B. Fernandez, M. Graña, F. Oterino, "On the Influence of the Prediction Horizon in Dynamic Matrix Control," International Journal of Control Science and Engineering, vol. 3(1): 22-30 , 2013

  This Journal introduces the method of trial and error method for determining the values of Prediction Horizon and Control Horizon. Steps are given to approach to the empirical formula derivation.

- P. Tatjewski, "Advanced Control of Industrial Processes: Structures and Algorithms," Springer Publisher, 2007

  This paper discussed about the value of prediction horizon for which the set point can be achieved in much smaller time and which is best suited for better responses.

Apart from above mentioned, these are also the part of literature review which helped in understanding the objective in much detailed

- Clarence W. De Silwa, "Modeling and Control of Engineering Systems," CRC Press
- P. E. Orukpe, "Basics of Model Predictive Control"

Chapter – 3

Model Predictive Control

MODEL PREDICTIVE CONTROL

Model Predictive Control (MPC) is an advanced system for control programming that has been being used in the process businesses in chemical plants and oil refineries since the 1980s. The primary point of interest of MPC is the way that it permits the current time slot to be improved, while keeping future time slots in record. This is accomplished by upgrading a limited time-slot, however just actualizing the current time slot. MPC can expect future occasions and can take control activities likewise.

This chapter includes the basic ideas of MPC, DMC, tuning parameters and their effects.

3.1 Overview [5]

The models utilized as a part of MPC represent the conduct of complex dynamical systems. The extra unpredictability of the MPC control calculation is not by and large expected to give satisfactory control of straight forward systems, which are frequently controlled well by non specific controllers.

MPC models anticipate the adjustment in the subordinate variables of the demonstrated system that will be brought about by changes in the independent variables. Independent variables can be balanced by controller continuously either by the set points of controller or the final control element. Independent variables that can't be balanced by the controller are utilized as disturbances. Dependent variables in these methodologies are different estimations that show either control objectives or methodology constraints.

MPC utilizes the present plant measurements, the present element condition of the procedure and the process variable targets to manipulate future changes in the input variables. These progressions are computed to hold the dependent variables near to target while regarding requirements on both autonomous and ward variables. The MPC normally conveys just the first change in every free variable to be actualized, and rehashes the figuring when the following change is needed.

3.2 Theory Behind: Receding Horizon Control

MPC is in view of cycles, limited horizon optimization of a process model. At time t, the present plant state is inspected and cost minimizing control methodology is figured (through a numerical minimization calculation) for a generally brief time horizon for future: [t, t+T]. Just the first step of the control method is executed, then the plant behaviour is tested again and the calculations are rehashed beginning from the new present state, yielding another control and new predicted state path. The prediction horizon continues being moved forward and hence MPC is additionally called Receding Horizon Control [2][5].

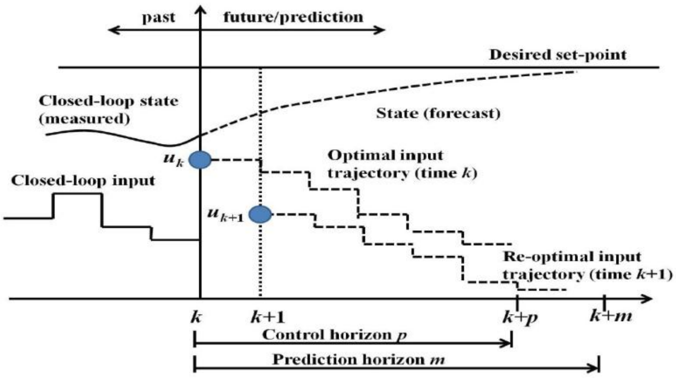

Fig. 1: Concept of MPC

3.3 Principle of MPC

Model Predictive Control (MPC) is a multivariable control calculation employing:

- an inward dynamic model of the methodology
- a background marked by past control moves and
- a optimized objective function J over the receding prediction horizon

to manipulate the ideal control moves.

The optimization cost function is given by:

$$J = \sum_{i=1}^{N} w_{xi}(r_i - x_i)^2 + \sum_{i=1}^{N} w_{ui}\Delta u_i{}^2$$

where,

x_i = *i* th controlled variable (e.g. measured level)

r_i = *i* th reference variable (e.g. required level)

u_i = *i* th manipulated variable (e.g. control valve)

w_{x_i} = weighting coefficient reflecting the relative significance of x_i

w_{u_i} = weighting coefficient penalizing relative large changes in u_i

3.4 Models for calculating the predicted values

3.4.1 Finite Impulse Response Model

By utilizing the convolution computation, a linear dynamic system can be spoken to by utilizing its impulse response sequence and is known as impulse response model [2]:

$$y_k = \sum_{i=1}^{\infty} h_i u_{k-i}$$

For practical use, this is so called finite impulse response (FIR) given as:

$$y_k = \sum_{i=1}^{N_m} h_i u_{k-i}$$

3.4.2 Finite Step Response Model

The impulse response sequence $(h_1, h_2, \dots, h_\infty)$ is related to step response $(a_1, a_2, \dots, a_{ss})$ according to following manner [2]:

$a_1 = h_1$

$a_2 = h_1 + h_2$

...

$a_n = h_1 + h_2 + \dots + h_n$

...

Thus, step response model can be written as

$$y_k = a_1 \Delta u_{k-1} + a_2 \Delta u_{k-2} + \cdots + a_\infty \Delta u_{k-\infty}$$

But for computation purpose, only finite terms are adopted which is known as finite step response model, i.e.

$$y_k = a_1 \Delta u_{k-1} + a_2 \Delta u_{k-2} + \cdots + a_{N_m} \Delta u_{k-N_m} + a_{N_m} u_{k-N_m-1}$$

3.5 Advantages and Limitation

3.5.1 Advantages of MPC

1. It can deal with the basic changes in the plant or process.
2. It permits consideration of plant requirement consequently, benefit is more.
3. Actuator limits can likewise be considered.
4. Non-minimal phase system with inverse reaction and unstable processes can be controlled viably.
5. It can deal with MIMO systems and multivariable control issues characteristically.

3.5.2 Limitations of MPC

1. A few MPC models are restricted to just steady, open-loop processes.
2. MPC frequently obliges countless coefficients to describe a response.
3. Some MPC models are figured for output disturbances, and they may not handle input disturbances well.
4. In the event that the prediction horizon is not figured accurately, control execution will be poor regardless of the possibility that the model is right.
5. A few systems have an extensive variety of working conditions that change every now and again. A nonlinear model must be utilized for better control execution for these systems.

3.6 Dynamic Matrix Control

In 1960s, Shell Oil Company first developed DMC and was intended its use in petroleum refineries. It is based on step response model [2] which is given as

$$y_k = s_1 \Delta u_{k-1} + s_2 \Delta u_{k-2} + \cdots + s_{N-1} \Delta u_{k-N+1} + s_N u_{k-N}$$

and re-written as

$$y_k = \sum_{i=1}^{N-1} s_i \Delta u_{k-i} + s_N u_{k-N}$$

where y_k is model prediction at time k, and u_{k-N} is the manipulated input N steps in the past. The 'corrected prediction' is then equal to actual measured output at step k,

$$y_k^c = y_k + d_k$$

for the *j*th step into future, we have

$$\underbrace{y_{k+j}^c}_{\substack{\text{Corrected}\\ \text{Prediction}}} = \underbrace{\sum_{i=1}^{j} s_i \Delta u_{k-i+j}}_{\substack{\text{effect of future}\\ \text{control moves}}} + \underbrace{\sum_{i=j+1}^{N-1} s_i \Delta u_{k-i+j} + s_N u_{k-N+j}}_{\text{effect of past control moves}} + \underbrace{d_{k+j}}_{\text{correction term}}$$

In matrix-vector form, a prediction horizon of P steps and a control horizon of M steps yields,

$$\underbrace{\begin{pmatrix} y_{k+1}^c \\ y_{k+2}^c \\ \cdots \\ y_{k+j}^c \\ \cdots \\ y_{k+P}^c \end{pmatrix}}_{\substack{\text{P*1}\\ \text{Corrected o/p}\\ \text{Predictions}}} = \underbrace{\begin{pmatrix} s_1 & 0 & 0 & \dots & 0 & 0 \\ s_2 & s_1 & 0 & \dots & 0 & 0 \\ & \dots & & \dots & & \\ s_j & s_{j-1} & s_{j-2} & \dots & \dots & s_{j-M+1} \\ & \dots & & \dots & & \\ s_P & s_{P-1} & s_{P-2} & \dots & \dots & s_{P-M+1} \end{pmatrix}}_{\substack{\text{P*M}\\ \text{dynamic matrix}}} \underbrace{\begin{pmatrix} \Delta u_k \\ \Delta u_{k+1} \\ \cdots \\ \Delta u_{k+M-1} \end{pmatrix}}_{\substack{\text{M*1}\\ \text{current and future}\\ \text{control moves}}}$$

$$
+\underbrace{\begin{pmatrix} s_2 & s_3 & s_4 & \dots & s_{N-2} & s_{N-1} \\ s_3 & s_4 & s_5 & \dots & s_{N-1} & 0 \\ \dots & & & & 0 & 0 \\ \dots & & & \dots & & \\ s_{j+1} & s_{j+2} & \dots & s_{N-1} & 0 & 0 \\ s_{P+1} & s_{P+2} & \dots & 0 & 0 & 0 \end{pmatrix}}_{\substack{\text{P*(N-2)} \\ \text{matrix}}}
\underbrace{\begin{pmatrix} \Delta u_{k-1} \\ \Delta u_{k-2} \\ \dots \\ \Delta u_{k-N+3} \\ \Delta u_{k-N+2} \end{pmatrix}}_{\substack{\text{(N-2)*1} \\ \text{past control} \\ \text{moves}}}
+ s_N \underbrace{\begin{pmatrix} \Delta u_{k-N+1} \\ \Delta u_{k-N+2} \\ \dots \\ \Delta u_{k-N+P} \end{pmatrix}}_{\substack{\text{P*1} \\ \text{past} \\ \text{inputs}}}
+ \underbrace{\begin{pmatrix} d_{k+1} \\ d_{k+2} \\ \dots \\ d_{k+P} \end{pmatrix}}_{\substack{\text{P*1} \\ \text{predicted} \\ \text{disturbances}}}
$$

which we can write in matrix-vector notation

$$
\underbrace{Y^c}_{\substack{\text{Corrected} \\ \text{Predicted} \\ \text{Outputs}}} = \underbrace{S_f \Delta u_f}_{\substack{\text{effect of} \\ \text{current and} \\ \text{future moves}}} + \underbrace{S_{past} \Delta u_{past} + s_N u_P}_{\text{effect of past moves}} + \underbrace{\mathrm{d}}_{\substack{\text{predicted} \\ \text{disturbances}}}
$$

3.7 Objective Function

Objective Function or Cost Function is a degree of execution of the procedure of the controller. It is obliged that the controlling system ought to take particular pattern. This is accomplished by minimizing the objective function or cost function. Each Cost Function contains the separate sub capacity which is obliged to be preferred.

3.7.1 Types of Cost Function

Different varieties of Cost Functions are available for example Absolute Value Objective Function, Standard Least-squares or Quadratic Objective Function, etc. [2]

3.7.1.1 *Quadratic Objective Function*

This sort of Objective Function is the total of squares of the predicted errors and the control moves. Control moves are characterized as the adjustments in control activity from step to step. Predicted errors are the contrasts between the set point and model-predicted outputs. For example, a quadratic objective function has a prediction horizon of length 2 and control horizon of length 1 then expression can be represented in the form

$$
\Phi = (r_{k+1} - x_{k+1})^2 + (r_{k+2} - y_{k+2})^2 + \mathrm{w}\, \Delta {u_k}^2
$$

Here, y is model predicted output, u is change in manipulated input from one sample to next, r is set point and w is weight for changes in manipulated variable. k denotes current sample.

For P and M, the least Squares Objective Function can be written as

$$\Phi \;=\; \sum_{i=1}^{P}(r_{k+1} - y_{k+1})^2 + \sum_{i=0}^{M-1} \Delta u_{k+1}{}^2$$

3.7.1.2 *Absolute Value Objective Function*

This is another objective function which just takes a whole of absolute values the estimations of the predicted errors and control moves. Despite the fact that this sort of objective function is genuinely straightforward when contrasted with quadratic objective function, the later is more suitable in its approach dealing with the non linear process models. For example, a quadratic objective function having prediction horizon of length 2 and control horizon of length 1, the expression can be expressed in the form

$$\Phi = |\,(r_{k+1} - \, y_{k+1})\,| + |\,(r_{k+2} - \, y_{k+2})\,| + \mathrm{w}\,|\,\Delta u_k\,|$$

Similarly to quadratic objective function, it has following form for P and M

$$\Phi = \sum_{i=1}^{P} |\,(r_{k+1} - \, y_{k+1})\,| + \mathrm{w} \sum_{i=0}^{M-1} |\,\Delta u_k|$$

The Optimization Problem under control is explained as an after effect of minimization of the objective function. This is gotten by altering the M control moves, subjecting to display comparisons and imperatives on the inputs and outputs.

Hence,

$$\mathrm{Min}_{\Delta \mathrm{u_k},\ldots,\Delta \mathrm{u_{k+M-1}}}\ \phi$$

3.7.2 Uses of Cost Function

Minimization of Cost Functions by least-squares method is by a wide margin the most widely recognized Cost function in MPC. Least squares method gives demonstrative arrangements for unconstrained issues.

The absolute value objective function is utilized as a part of a couple of calculations in light of the fact that straight programming issue results during optimization. Linear programming is solved in huge scale designation and booking issues. Likewise linear programming is valuable to choose how much and what item to deliver at every plant. On the other hand, the straight programming methodology is not helpful for model predictive control. It is on the grounds that the manipulated variable regularly moves from one extreme to other.

3.8 Tuning Parameters of DMC

Every controller design has some layout parameters, which can be tuned to get the desired response of the controller. These parameters are known as the tuning parameters of the controller. The going with standards is basically used to tune a DMC:

1 .The model horizon N should be chosen so that N t ≥ open loop settling time. Value of N is typically processed in the range 20 - 70.

2. The Prediction Horizon (p) decides how far into the future the control objective reaches. Expanding p makes the control more precise yet builds the processing. The most suggested estimation of p is when p=N+ m.

3. The Control Horizon (m) focus the no. of the control activities figured into what's to come. Too extensive estimation of m reasons exorbitant control activity. Little estimation of Nu makes the controller heartless of noise.

Chapter – 4

Quadruple Tank System

QUADRUPLE TANK SYSTEM

This chapter gives a brief introduction about the experiment lab apparatus, mathematical modeling of tank systems and some observations taken.

4.1 Four Tank Systems

A modified four tank system was planned and developed to give control system engineers research facility involvement with key multivariable control ideas. The general type of plant model making can keep the properties of existing four tanks about multivariable zero areas.

Fig. 2: Experimental Setup of Four Tank Systems

The modified quadruple tank process is a mix of two double tank system given in Fig. 2. This setup comprise of a water supply tank with two variable speed positive displacement pump for water course fitted with stream dampers, four transparent process tanks fitted with level transmitters, rotameters. Procedure signals from the tank level transmitters are interfaced with PC. Control calculation running on the PC sends output to the individual pump variable recurrence drive through interfacing units. Two tanks are placed at the bottom side and two on above. All four tanks are connected to the pumps where they receive water from the water reservoir. Above two tanks empties water to below tanks. All the pipe systems are connected through the valve system. This system is connected to PC via data acquisition card and also has the display unit on the experimental setup.

4.2 Mathematical Modeling of Four tank systems [4]

For the non-interacting two tank systems:

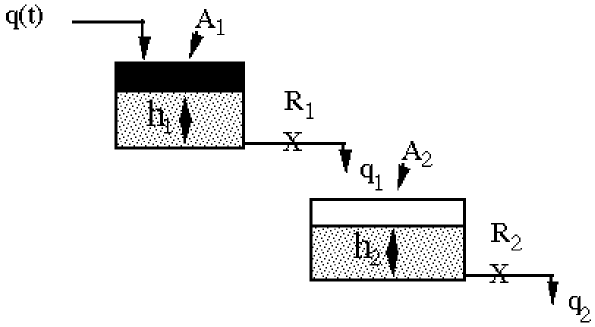

Fig. 3: Two Tank Non-interacting systems

Mass balance around tank 1: $A_1(dh_1/dt) = q_i - q_1$

For resistance element (valve 1): $q_1 = h_1/R_1$

Eliminating q_1 from equation: $A_1(dh_1/dt) = q_i - h_1/R_1$

Putting the above equation in derivation variable form:

$$A_1{*}(dH_1/dt) = Q_i - H_1/R_1$$

$$H_1(s)/Q_i(s) = R_1/(A_1R_1s+1) = K_1/(\tau_1 s+1)$$

$$\text{where } K_1 = R_1 \text{ and } \tau_1 = A_1R_1$$

Mass balance around tank 2: $A_2(dh_2/dt) = q_1 - q_2$ and $q_2 = h_2/R_2$

Expressing the above equation using derivation variables:

$$H_2(s)/Q_1(s) = R_2/(A_2R_2s+1) = K_2/(\tau_2 s+1)$$

Thus,

$$H_2(s)/Q_i(s) = K_2/(\tau_1 s+1)(\tau_2 s+1)$$

In the experimental tank used, following data are used

$$\tau_1 = \tau_2 = \tau$$

$$g = 980 \text{ cm/s}^2$$

$$a = 7.068 \text{ cm}^2$$

$$A = 176.71 \text{ cm}^2$$

$$1 \text{ LPH} = 0.2777 \text{ cm}^3\text{/s}$$

For the interacting tank systems

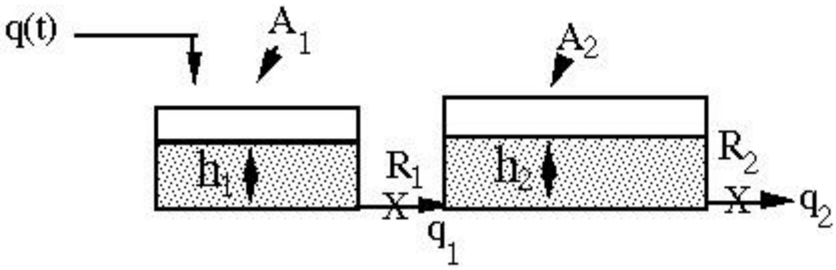

Fig. 4: Two Tank Interacting system

Two tank in series whose liquid levels interact.

For resistance element (valve 1): $q_1 = (1/R_1)*(h_1-h_2)$

Transfer Function for interacting system is given as

$$H_2(s)/Q_i(s) = R_2/(\tau^2 s^2+3\tau s+1)$$

$$\text{where } \tau = A_1R_1$$

$$R = h/q = h/(k\sqrt{h})$$

4.3 Observation and Transfer Function

Taking the two non interacting tanks and using mathematical modelling following transfer functions are obtained

Flow (LPH)	Height (cm)	Transfer Function
350	44	$0.45/(6323.43s^2+159.04s+1)$
320	39	$0.43/(5772.96s^2+151.96s+1)$
290	34	$0.42/(5507.12s^2+148.42s+1)$
260	25	$0.346/(3738.09s^2+122.28s+1)$
230	16.25	$0.25/(1951s^2+88.34s+1)$
200	9.25	$0.16/(799.19s^2+56.54s+1)$
170	5	$0.10/(315.41s^2+35.52s+1)$
140	2	$0.05/(77.96s^2+17.66s +1)$
110	0.5	$0.016/(7.95s^2+5.64s +1)$
80	0	0

Table 1: Transfer Function of two non interacting tank systems

Taking the two interacting tanks and using mathematical modelling following transfer functions are obtained

Flow (LPH)	Height (cm)	Transfer Function
350	44	$0.45/(6323.43s^2+238.56s+1)$
320	39	$0.43/(5772.96s^2+227.94s+1)$
290	34	$0.42/(5507.12s^2+222.63s+1)$
260	25	$0.346/(3738.09s^2+183.42s+1)$
230	16.25	$0.25/(1951s^2+132.51s+1)$
200	9.25	$0.16/(799.19s^2+84.81s+1)$
170	5	$0.10/(315.41s^2+53.01s+1)$
140	2	$0.05/(77.96s^2+26.49s +1)$
110	0.5	$0.016/(7.95s^2+8.46s +1)$
80	0	0

Table 2: Transfer Function of two interacting tank systems

Using this transfer function, we will acquire State Space Matrix and then using MATLAB window, simulations are done for the purpose of congruity with some theoretical approaches.

Chapter – 5

Linearity of Controller

LINEARITY OF CONTROLLER

This chapter deals with the simulation results which are collected using the transfer function obtained in the previous chapter. Different time constant processes are used to obtain the conclusion. All responses are based on DMC tuning method.

5.1 Simulations and Results

The MATLAB coding which is used for getting responses is given in Annexure 1. Values of A, B, C, D matrix are changed for different time constants in MATLAB coding. Taking the transfer function at 260 LPH (time constant (τ_p) = 62.5s), following responses are obtained

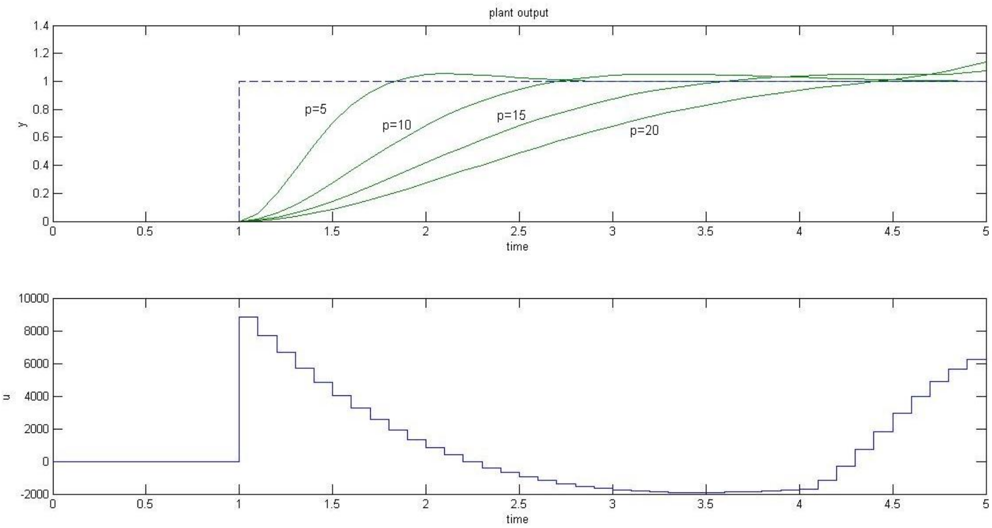

Fig. 5: For m=1, p=5:5:20, n=50 (τ_p= 62.5s)

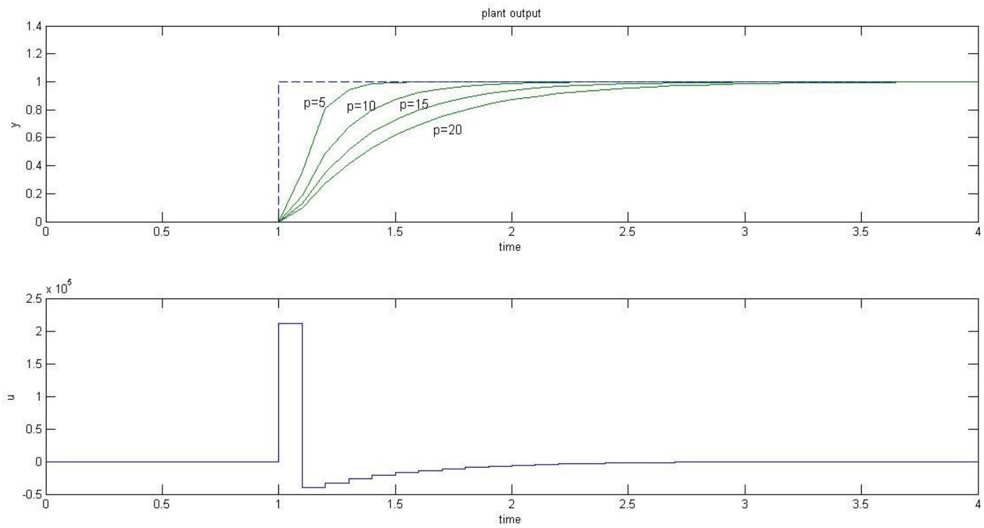

Fig. 6: For m=2, p=5:5:20, n=50 (τ_p= 62.5s)

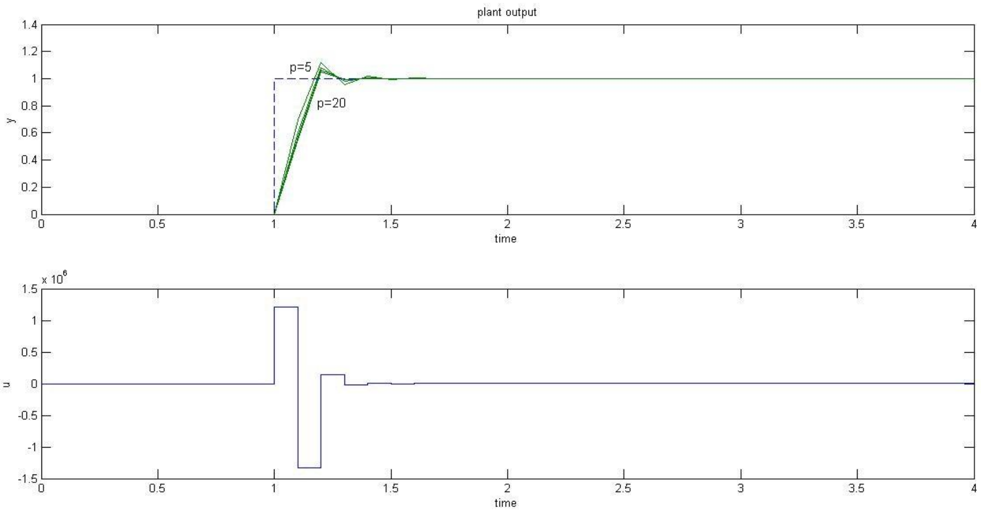

Fig. 7: For m=3, p=5:5:20, n=50 (τ_p= 62.5s)

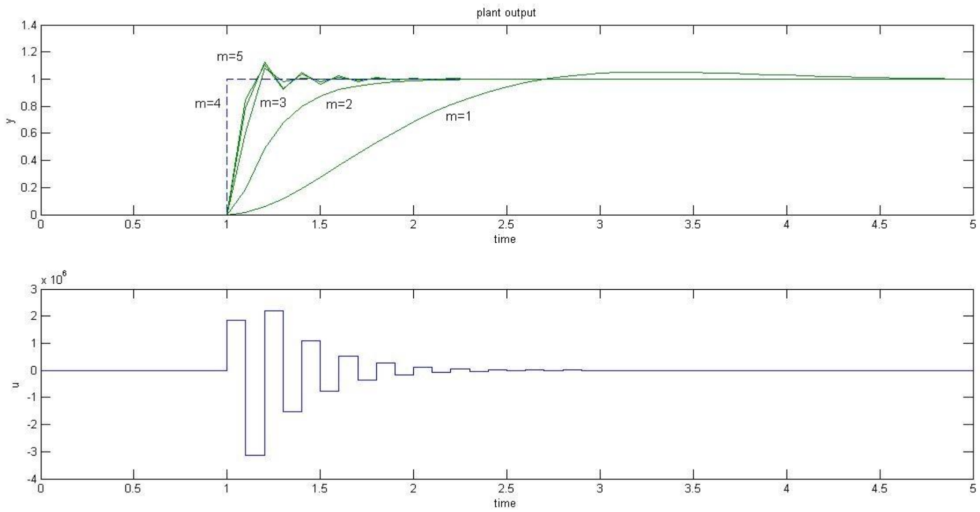

Fig. 8: For m=1:5, p=10, n=50 (τ_p= 62.5s)

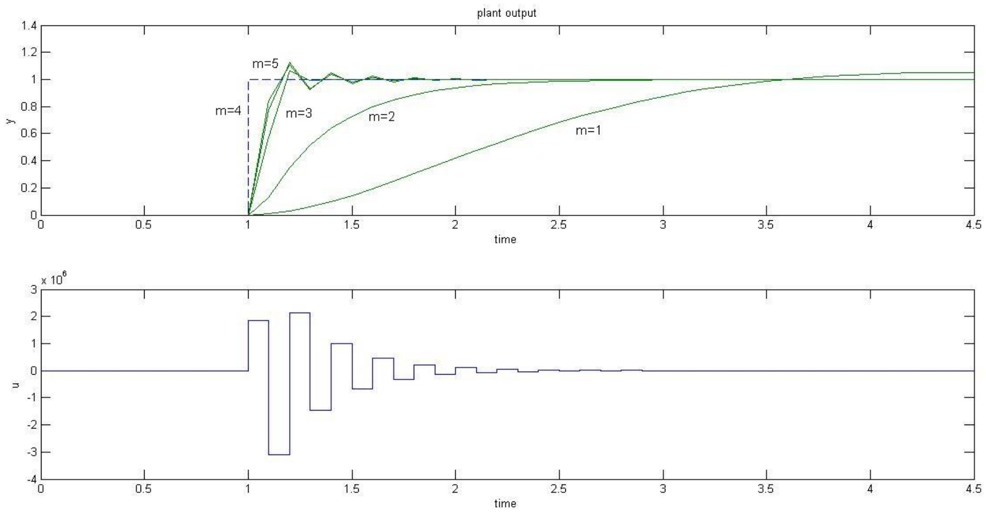

Fig. 9: For m=1:5, p=15, n=50 (τ_p= 62.5s)

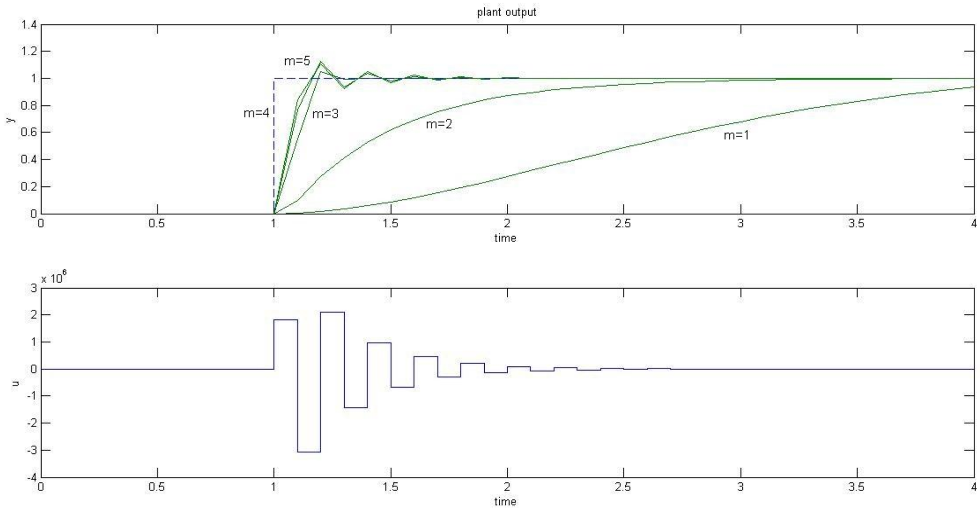

Fig. 10: For m=1:5, p=20, n=50 (τ_p= 62.5s)

From the above responses following observational data are obtained

p	settling time (s)			% overshoot		
	m=1	m=2	m=3	m=1	m=2	m=3
5	1.9	0.6	0.6	5.4%	-	11.9%
10	3.8	1.2	0.4	5.2%	-	8.1%
15	3.9	1.7	0.4	6.8%	-	6%
20	3.9	2.6	0.4	-	-	4.8%

m	settling time (s)			% overshoot		
	p=10	p=15	p=20	p=10	p=15	p=20
1	3.8	3.9	3.9	5.2%	6.8%	-
2	1.2	1.7	2.6	-	-	-
3	0.4	0.4	0.4	8.1%	6%	4.8%
4	0.9	0.9	0.8	12.3%	12.4%	12.4%
5	1.4	1.3	0.9	10.4%	10.7%	10.8%

Table 3: Observations for time constant = 62.5s

Now taking different transfer function at same 260 LPH having different time constant (τ_p= 1.12s) following responses are collected.

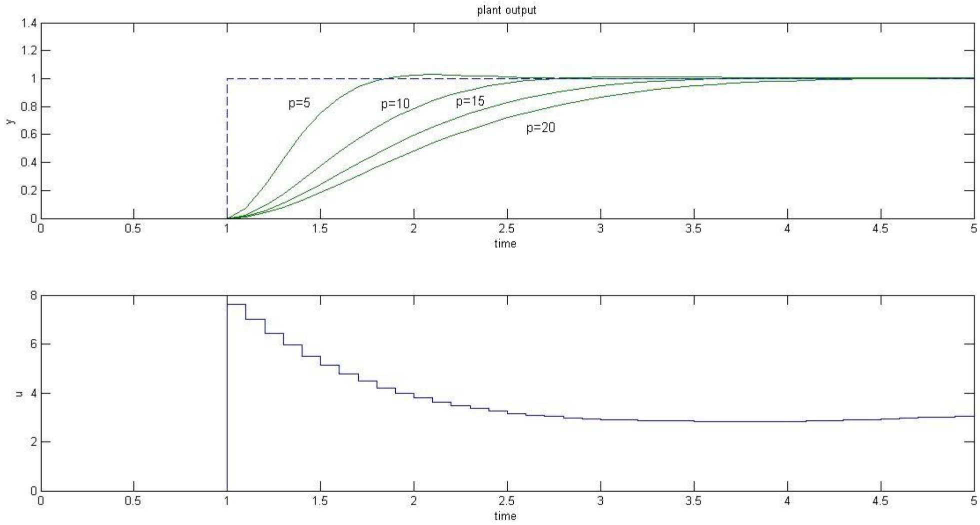

Fig. 11: For m=1, p=5:5:20, n=50 (τ_p= 1.12s)

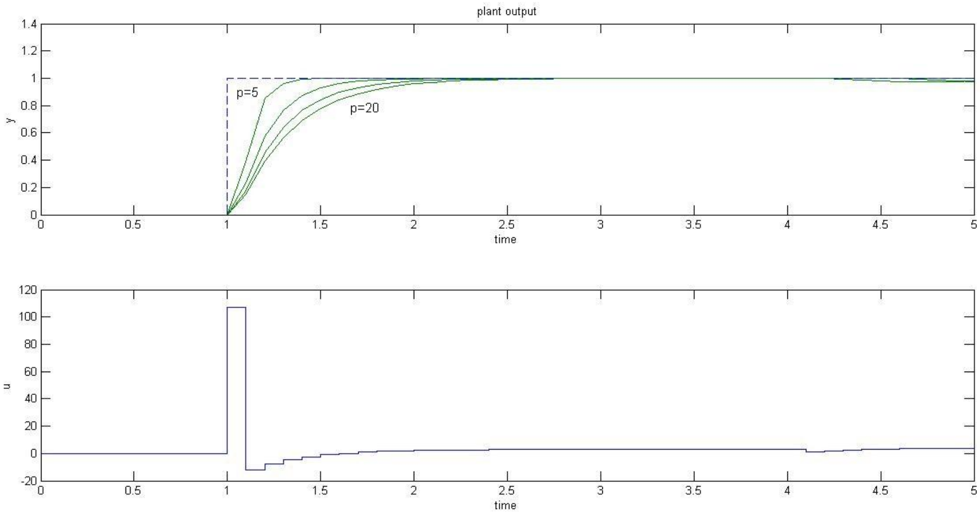

Fig. 12: For m=2, p=5:5:20, n=50 (τ_p= 1.12s)

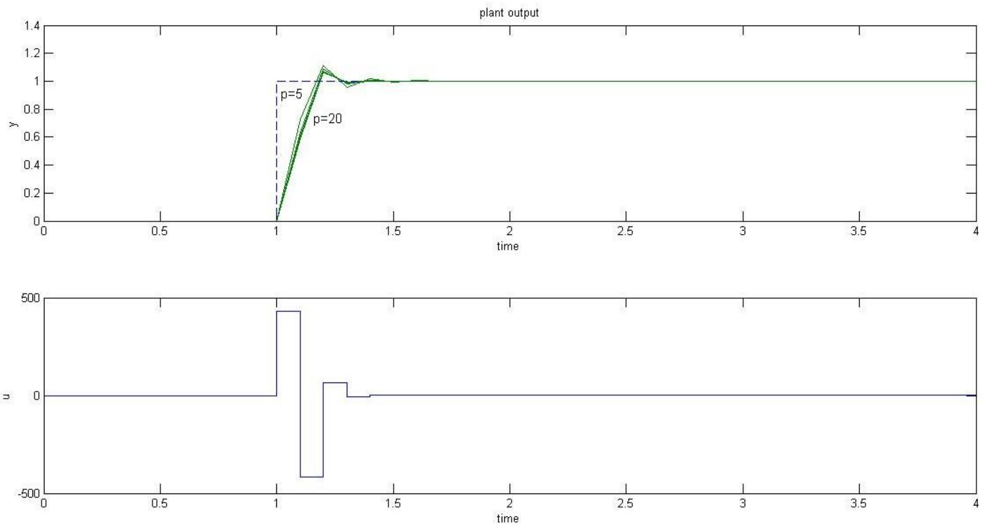

Fig. 13: For m=3, p=5:5:20, n=50 (τ_p= 1.12s)

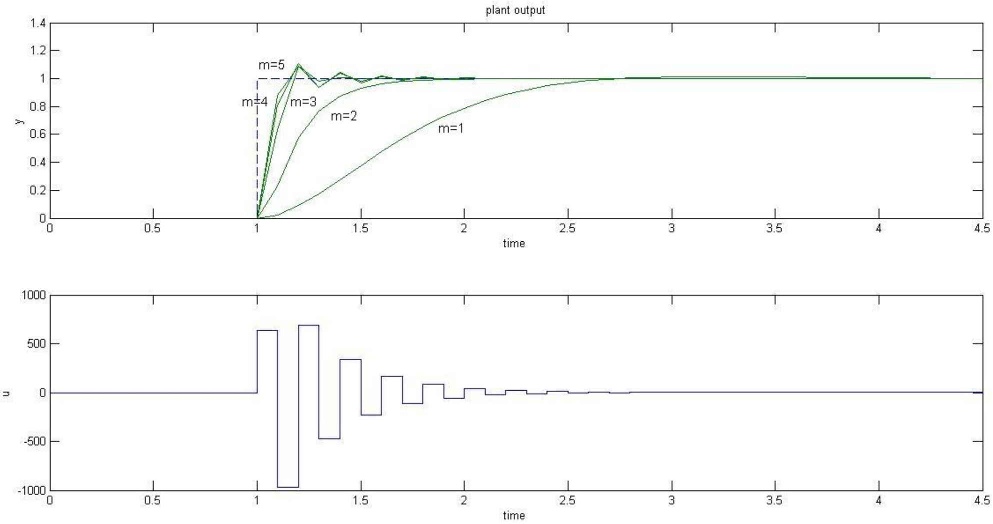

Fig. 14: For m=1:5, p=10, n=50 (τ_p= 1.12s)

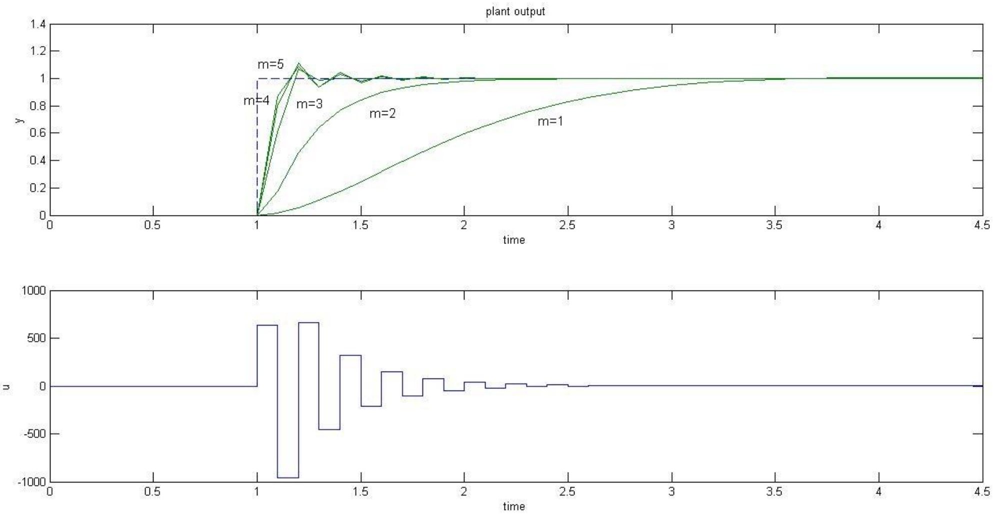

Fig. 15: For m=1:5, p=15, n=50 (τ_p= 1.12s)

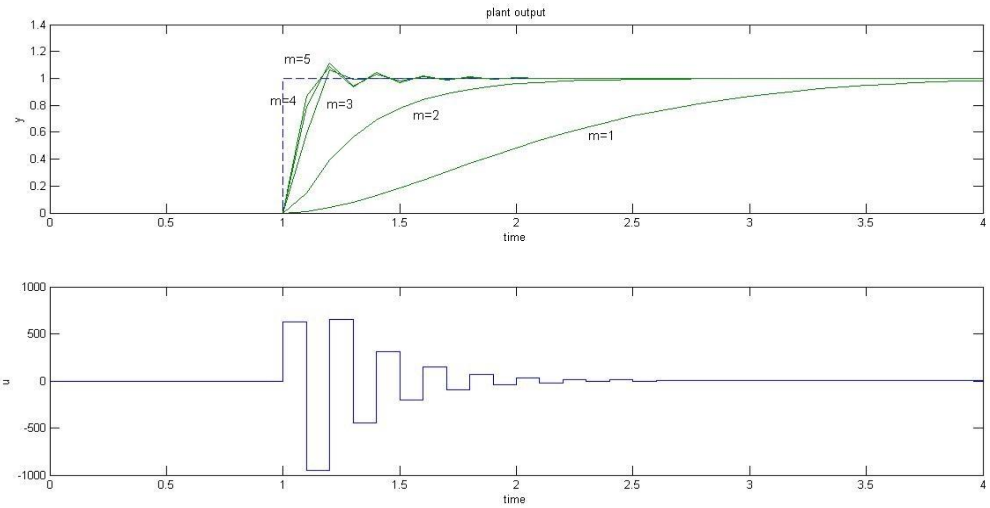

Fig. 16: for m=1:5, p=20, n=50 (τ_p= 1.12s)

From the above responses following observational data are obtained

p	settling time (s)			% overshoot		
	m=1	m=2	m=3	m=1	m=2	m=3
5	1.7	0.5	0.7	2.9%	-	11.2%
10	3.3	0.9	0.5	1.4%	-	8.5%
15	3.5	1.4	0.4	0.7%	-	6.9%
20	3.8	1.5	0.4	-	-	6%
m	settling time (s)			% overshoot		
	p=10	p=15	p=20	p=10	p=15	p=20
1	3.3	3.5	3.8	1.4%	0.7%	-
2	1.0	1.4	1.5	-	-	-
3	0.5	0.4	0.4	8.5%	6.9%	6%
4	0.8	0.8	0.9	10.9%	11.1%	11.2%
5	1	1	1.1	8.6%	8.9%	9.1%

Table 4: Observations for time constant = 1.12s

Similarly taking different transfer function at same 260 LPH having different time constant (τ_p= 0.272s) following responses are collected.

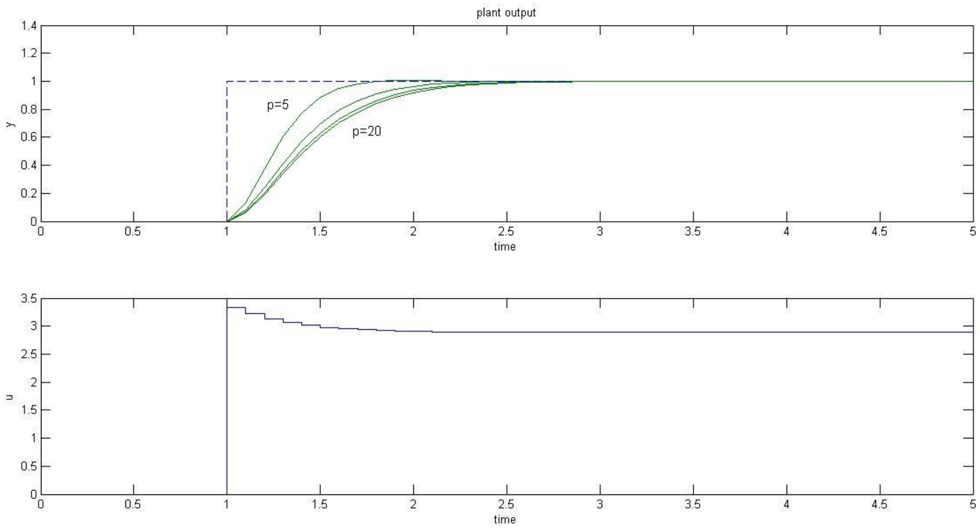

Fig. 17: For m=1, p=5:5:20, n=50 (τ_p= 0.272s)

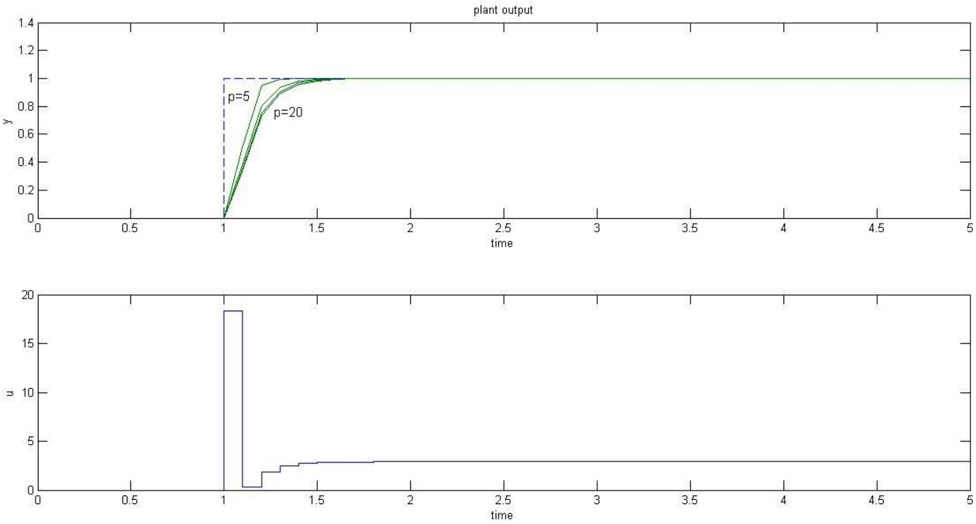

Fig. 18: For m=2, p=5:5:20, n=50 (τ_p= 0.272s)

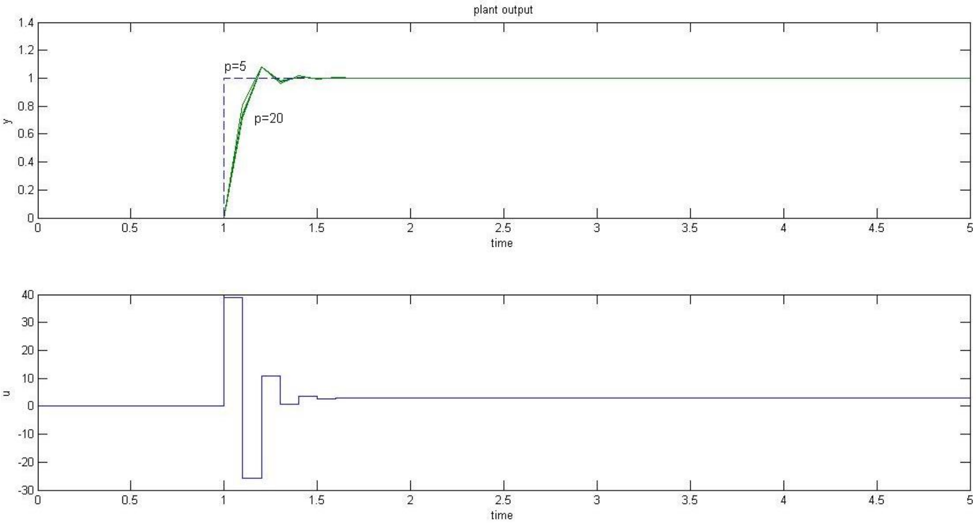

Fig. 19: For m=3, p=5:5:20, n=50 (τ_p= 0.272s)

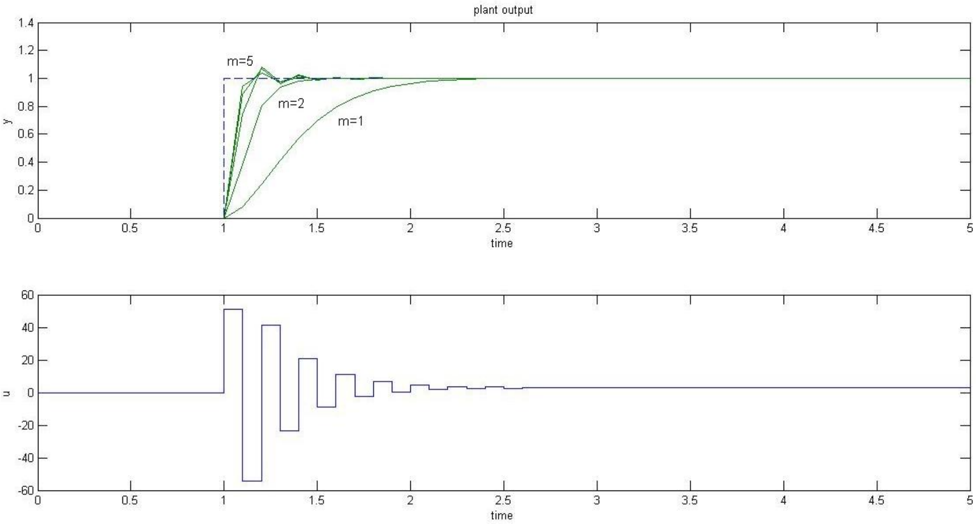

Fig. 20: For m=1:5, p=10, n=50 (τ_p= 0.272s)

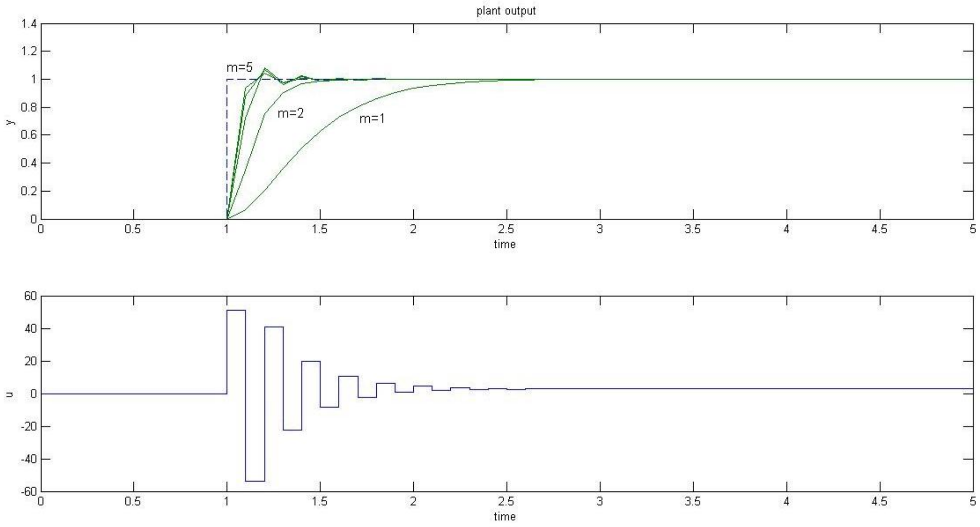

Fig. 21: For m=1:5, p=15, n=50 (τ_p= 0.272s)

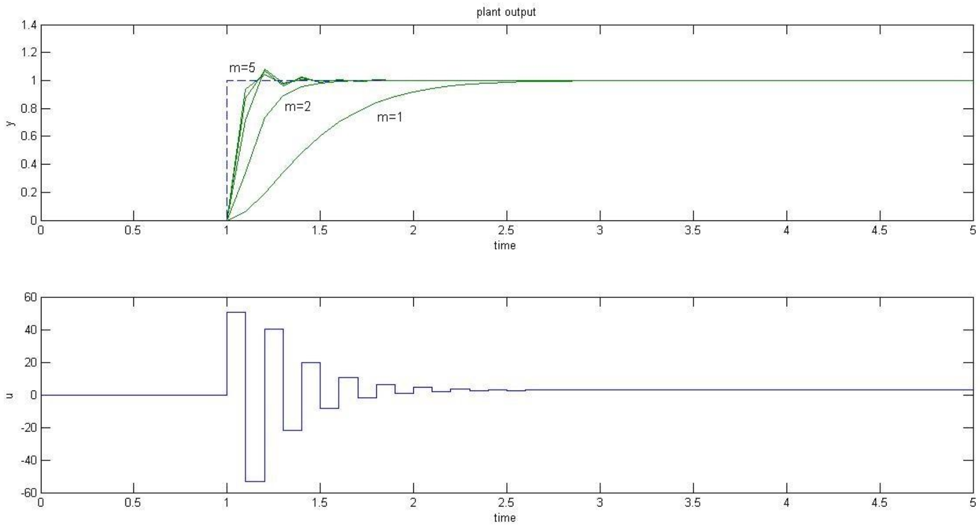

Fig. 22: For m=1:5, p=20, n=50 (τ_p= 0.272s)

From the above responses following observational data are obtained

p	settling time (s)			% overshoot		
	m=1	m=2	m=3	m=1	m=2	m=3
5	1.1	0.4	0.6	-	-	8.4%
10	1.4	0.6	0.5	-	-	8.3%
15	1.6	0.7	0.5	-	-	8%
20	1.6	0.6	0.5	-	-	7.8%

m	settling time (s)			% overshoot		
	p=10	p=15	p=20	p=10	p=15	p=20
1	1.4	1.6	1.6	-	-	-
2	0.6	0.7	0.6	-	-	-
3	0.5	0.5	0.5	8.3%	8%	7.8%
4	0.8	0.8	0.8	6.6%	6.9%	7%
5	0.8	0.8	0.9	4%	4.2%	4.3%

Table 5: Observations for time constant = 0.272s

5.2 Data Analysis

Based on the above obtained table, following analysis can be made

1. For p=5:5:20 with different values of m, same type of responses are observed for each time constant.
2. In m=2, no overshoots are observed for every responses. Therefore, control horizon should be around 2 for better simulations outputs or responses.
3. With small prediction horizon, set point is being accomplished in much smaller time and is most appropriate for better reactions [6].

5.3 Linearity of Controller

On plotting the graph between Settling Time V/s Time Constant and percentage Overshoot V/s Time Constant, we can observe that the linear plots are obtained which shows that for any process with the same tuning parameters, we will get the same type of responses every time.

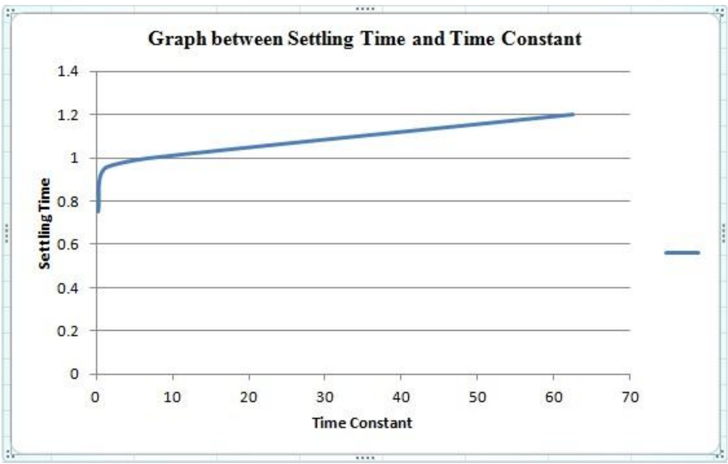

Fig. 23: Graph Plot between Settling Time V/s Time Constant

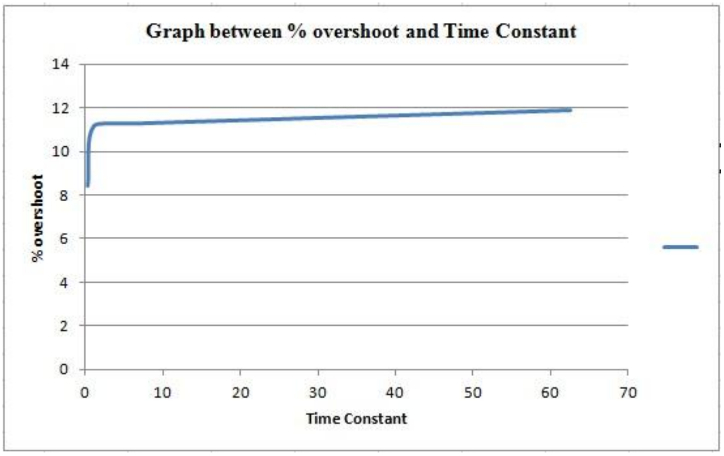

Fig. 24: Graph Plot between % overshoot V/s Time Constant

As we can see that both settling time and % overshoot increases with time constant linearly over a large time interval proves that the behaviour of the process remains same for any time constant, only the value of manipulated variables will change accordingly [8].

Chapter – 6

Derivation of Empirical Formula

DERIVATION OF EMPERICAL FORMULA

This chapter deals with the formulation of generalized formula which can be used for the calculation of values of prediction horizon and control horizon for any process. Also the analysis of Rise Time, Peak Time, Settling Time and Percentage Overshoot has been observed with respect to prediction horizon under different control horizon.

6.1 Effect of tuning Parameters

Various tuning parameters are changed to get effective responses or the desired responses which can be applied to real time applications. These effects show the direct relationship with the time constant.

Taking the transfer function at 260 LPH (τ_p=1.12s), different responses are obtained by taking different prediction horizon and keeping control horizon constants.

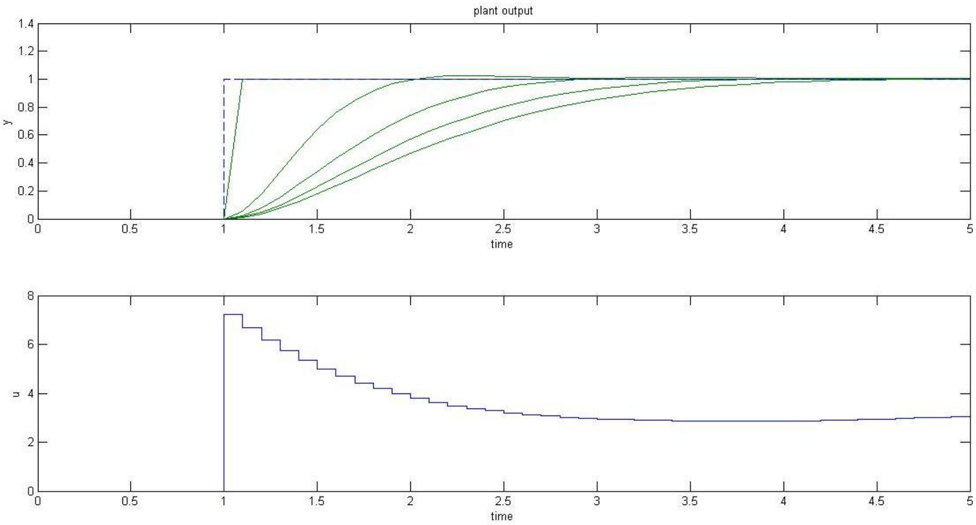

Fig. 25: For m=1, p=1:5:21, n=50

Following data are obtained from the graph

	p=1	p=6	p=11	p=16	p=21
Rise Time (sec)	0.10	0.90	1.80	2.40	3.20
Peak Time (sec)	0.15	1.20	2.40	3.20	3.50
Settling Time (sec)	0.15	2.00	3.00	3.20	3.50
%age Overshoot	-	2.50%	1.20%	-	-

Table 6: Data for m=1 and different values of p (τ_p=1.12s)

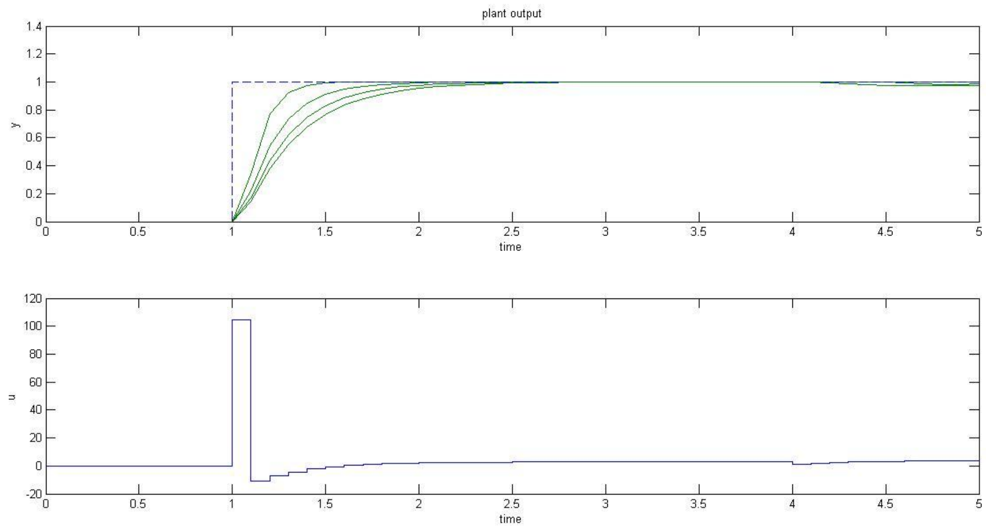

Fig. 26: For m=2, p=1:5:21, n=50

Following data are obtained from the graph

	p=1	p=6	p=11	p=16	p=21
Rise Time (sec)	-	0.40	0.70	0.80	0.95
Peak Time (sec)	-	0.55	1.10	1.40	1.70
Settling Time (sec)	-	0.55	1.10	1.40	1.70
%age Overshoot	-	-	-	-	-

Table 7: Data for m=2 and different values of p (τ_p=1.12s)

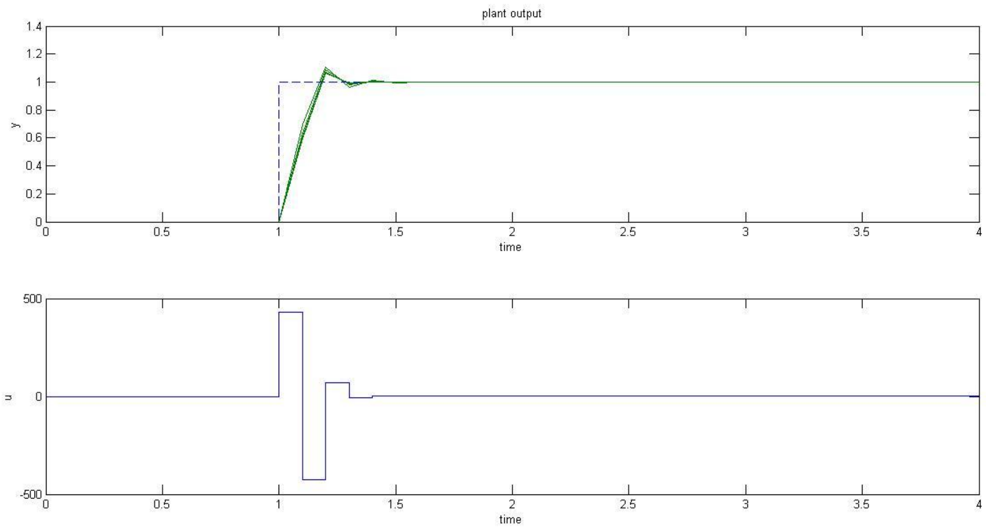

Fig. 27: For m=3, p=2:4:18, n=50

Following data are obtained from the graph

	p=2	p=6	p=10	p=14	p=18
Rise Time (sec)	-	0.15	0.19	0.20	0.20
Peak Time (sec)	-	0.22	0.21	0.21	0.21
Settling Time (sec)	-	0.50	0.40	0.40	0.30
%age Overshoot	-	10.60%	8.50%	7.20%	6.30%

Table 8: Data for m=3 and different values of p (τ_p=1.12s)

According to the data obtained, graphs are plotted for different tuning parameters and prediction horizon. These graphs are studied and conclusions are being made to obtain the generalized formula.

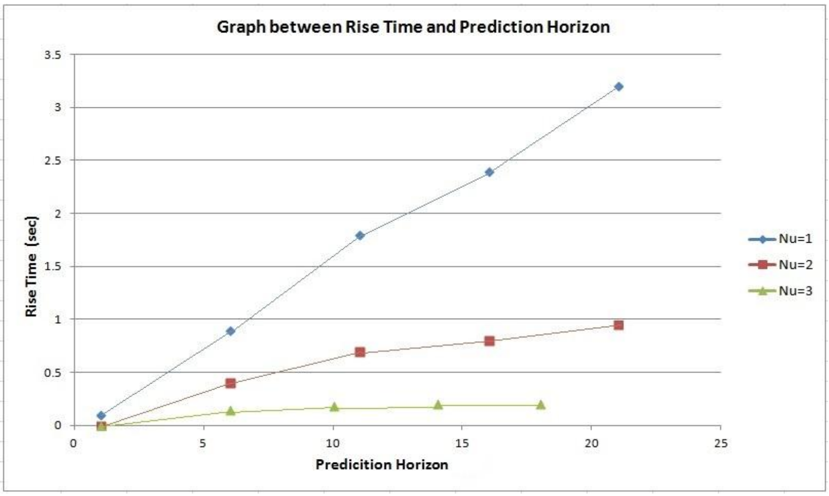

Fig. 28: Effect of Rise time w.r.t. prediction horizon

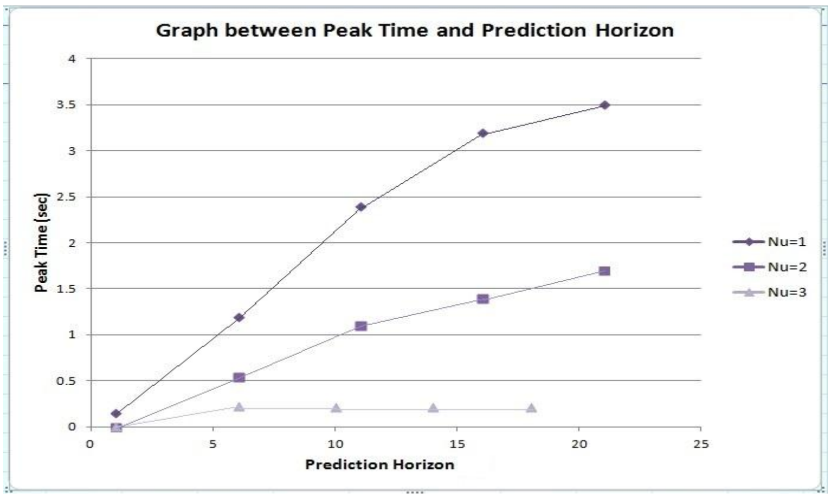

Fig. 29: Effect of Peak time w.r.t. prediction horizon

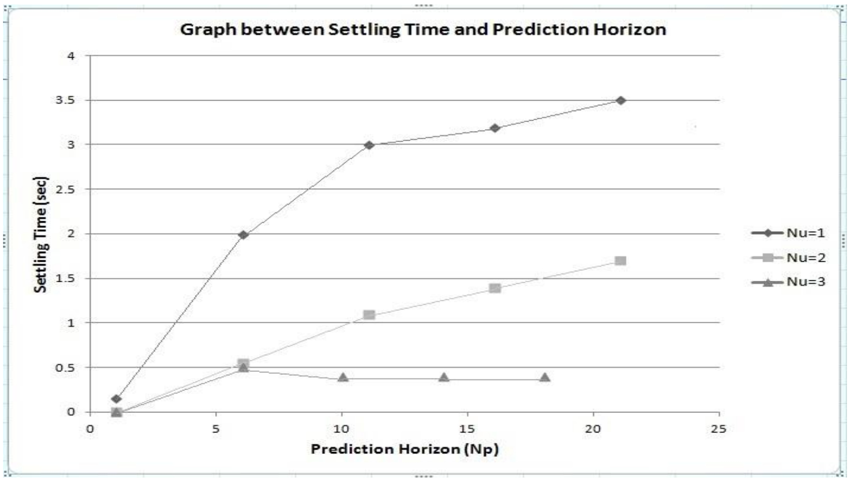

Fig. 30: Effect of Settling time w.r.t. prediction horizon

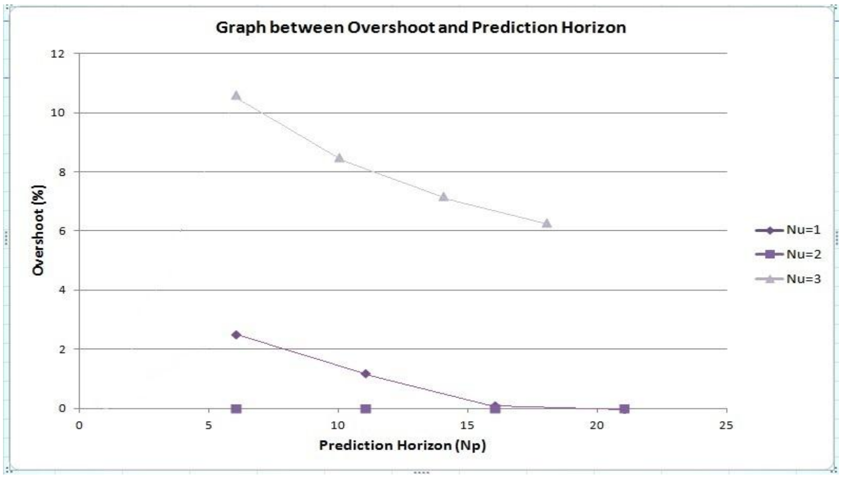

Fig. 31: Effect of Percentage Overshoot w.r.t. prediction horizon

Now taking different transfer function at 260 LPH (τ_p=62.5s), different responses are obtained by taking different prediction horizon and keeping control horizon constants.

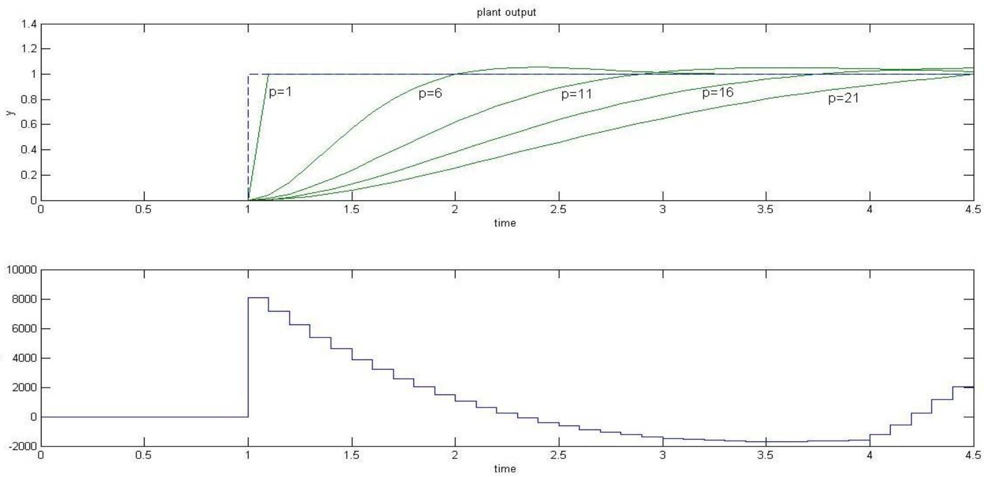

Fig. 32: For m=1, p=1:5:21, n=50

Following data are collected from the graph

	p=1	p=6	p=11	p=16	p=21
Rise Time (sec)	0.15	0.80	0.60	undefined	undefined
Peak Time (sec)	0.20	1.40	2.60	undefined	undefined
Settling Time (sec)	0.20	2.20	3.60	undefined	undefined
%age Overshoot	-	5.30%	5.10%	undefined	undefined

Table 9: Data for m=1 and different values of p (τ_p=62.5s)

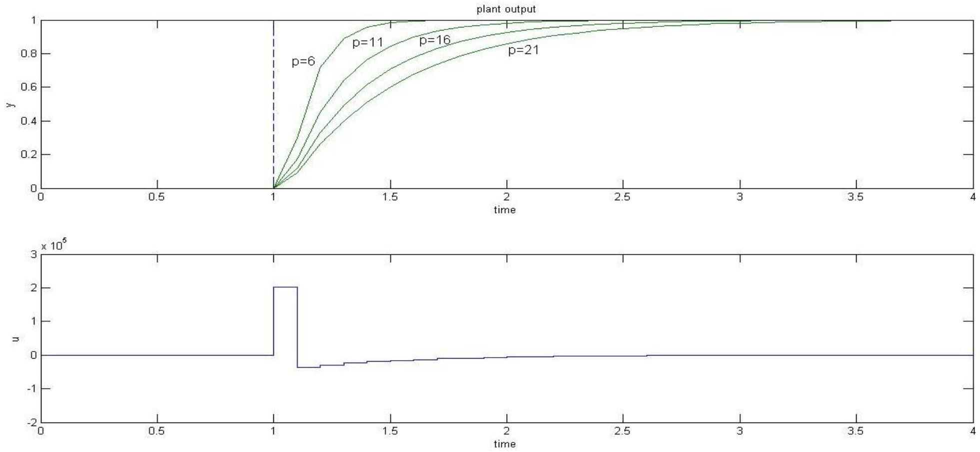

Fig. 33: For m=2, p=1:5:21, n=50

Following data are obtained from the graph

	p=1	p=6	p=11	p=16	p=21
Rise Time (sec)	-	0.30	0.80	1.40	1.70
Peak Time (sec)	-	0.70	1.40	2.10	2.70
Settling Time (sec)	-	0.70	1.40	2.1	2.70
%age Overshoot	-	-	-	-	-

Table 10: Data for m=2 and different values of p (τ_p=62.5s)

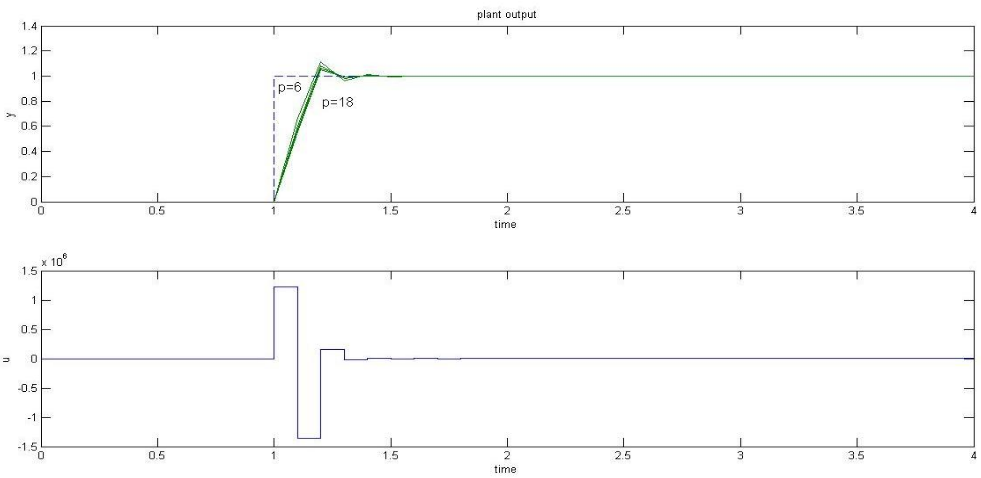

Fig. 34: For m=3, p=2:4:18, n=50

Following data are obtained from the graph

	p=2	p=6	p=10	p=14	p=18
Rise Time (sec)	-	0.18	0.19	0.20	0.20
Peak Time (sec)	-	0.22	0.22	0.21	0.21
Settling Time (sec)	-	0.40	0.43	0.47	0.52
%age Overshoot	-	11.00%	8.10%	6.40%	5.20%

Table 11: Data for m=3 and different values of p (τ_p=62.5s)

According to the data obtained, graphs are plotted for different tuning parameters and prediction horizon. These graphs are studied and conclusions are being made to obtain the generalized formula.

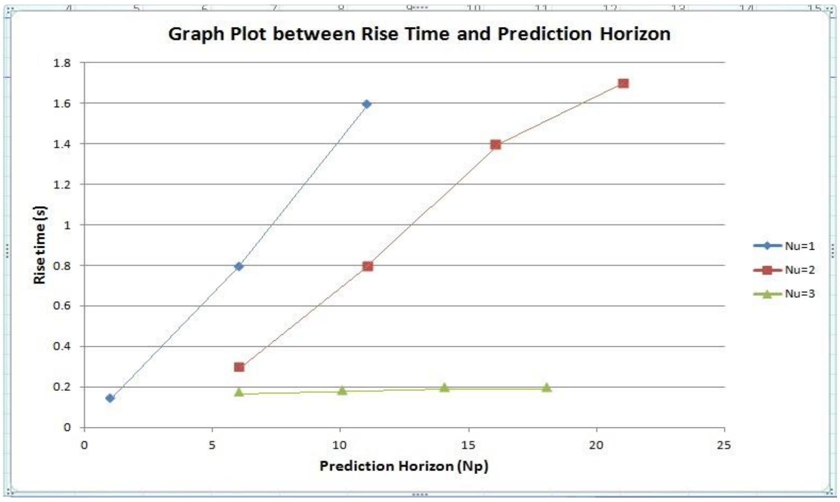

Fig. 35: Effect of Rise time w.r.t. prediction horizon

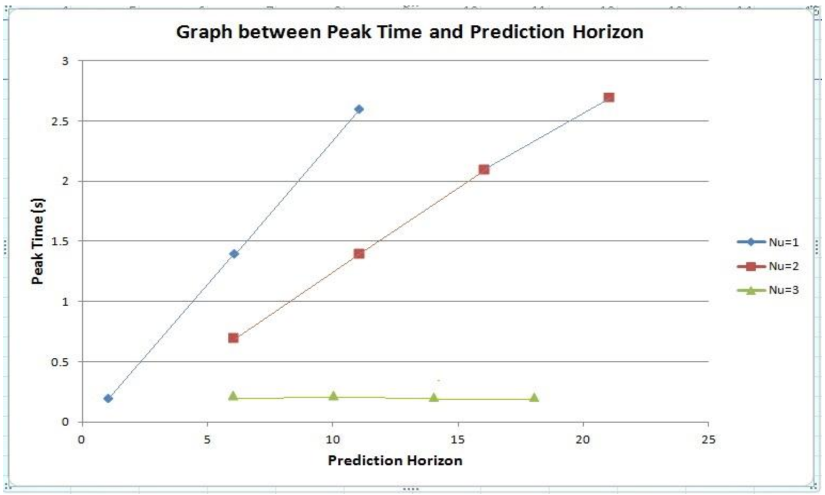

Fig. 36: Effect of Peak time w.r.t. prediction horizon

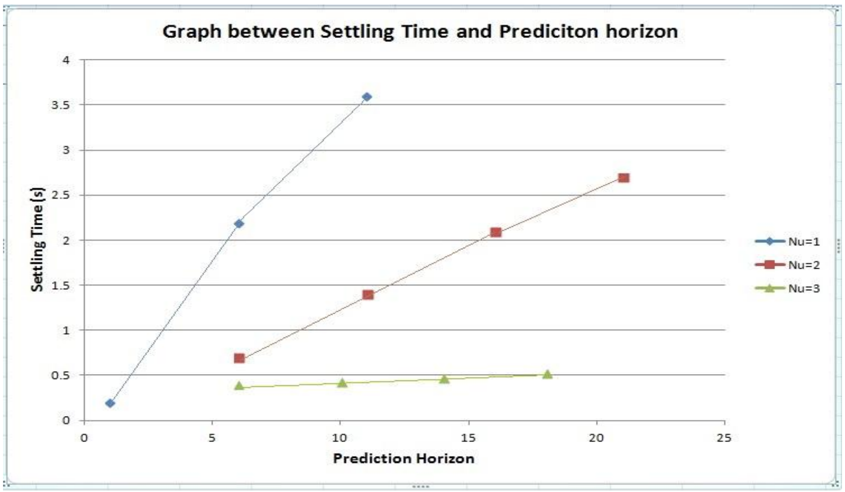

Fig. 37: Effect of Settling time w.r.t. prediction horizon

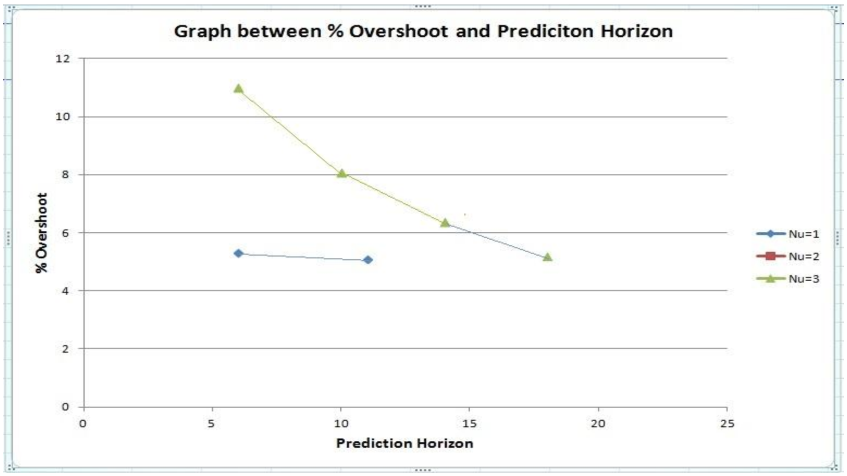

Fig. 38: Effect of Percentage overshoot w.r.t. prediction horizon

Similarly taking another transfer function at 260 LPH (τ_p=0.272s), different responses are obtained by taking different prediction horizon and keeping control horizon constants.

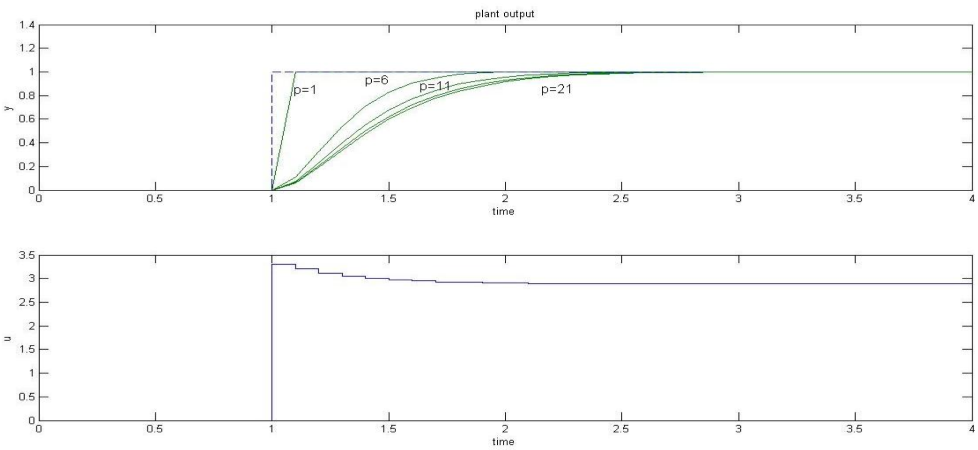

Fig. 39: For m=1, p=1:5:21, n=50

Following data are obtained from the graph

	p=1	p=6	p=11	p=16	p=21
Rise Time (sec)	0.10	0.65	0.80	0.95	1.1
Peak Time (sec)	0.20	0.95	1.40	1.60	1.90
Settling Time (sec)	0.20	0.95	1.40	1.60	1.90
%age Overshoot	-	-	-	-	-

Table 12: Data for m=1 and different values of p (τ_p=0.272s)

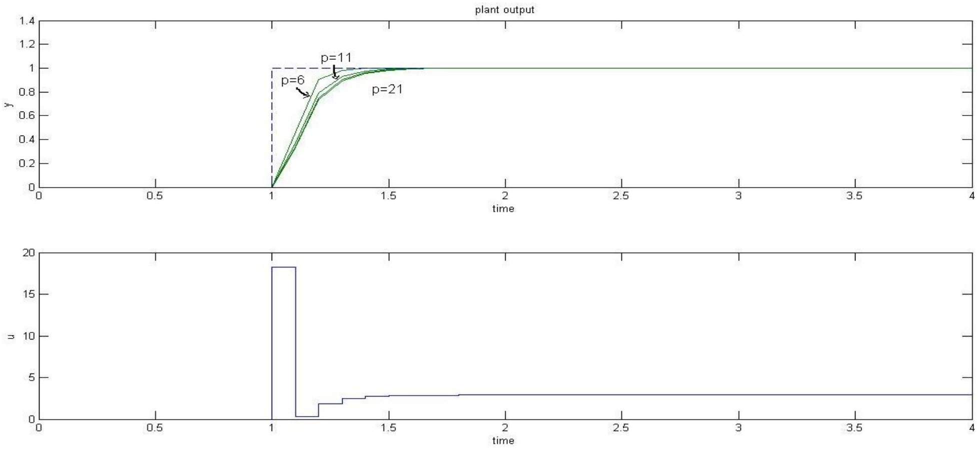

Fig. 40: For m=2, p=1:5:21, n=50

Following data are obtained from the graph

	p=1	p=6	p=11	p=16	p=21
Rise Time (sec)	-	0.20	0.30	0.40	0.45
Peak Time (sec)	-	0.40	0.50	0.60	0.70
Settling Time (sec)	-	0.40	0.50	0.60	0.70
%age Overshoot	-	-	-	-	-

Table 13: Data for m=2 and different values of p (τ_p=0.272s)

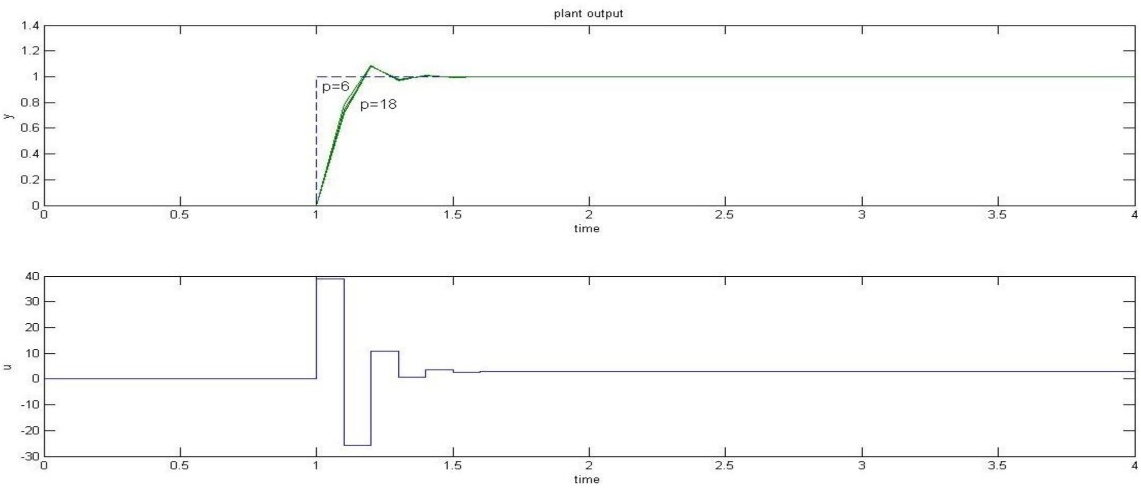

Fig. 41: For m=3, p=2:4:18, n=50

Following data are obtained from the graph

	p=2	p=6	p=10	p=14	p=18
Rise Time (sec)	-	0.17	0.18	0.19	0.20
Peak Time (sec)	-	0.30	0.30	0.30	0.30
Settling Time (sec)	-	0.38	0.40	0.45	0.50
%age Overshoot	-	8.60%	8.30%	8.00%	7.90%

Table 14: Data for m=3 and different values of p (τ_p=0.272s)

According to the data obtained, graphs are plotted for different tuning parameters and prediction horizon. These graphs are studied and conclusions are being made to obtain the generalized formula.

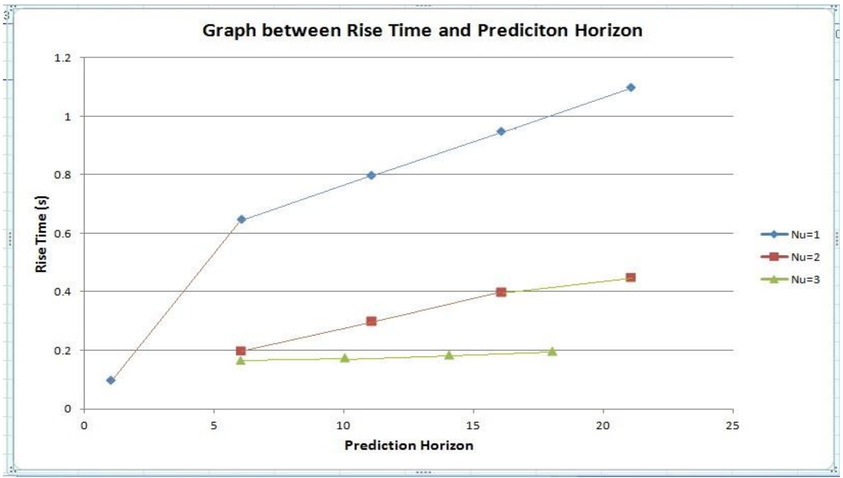

Fig. 42: Effect of Rise time w.r.t. prediction horizon

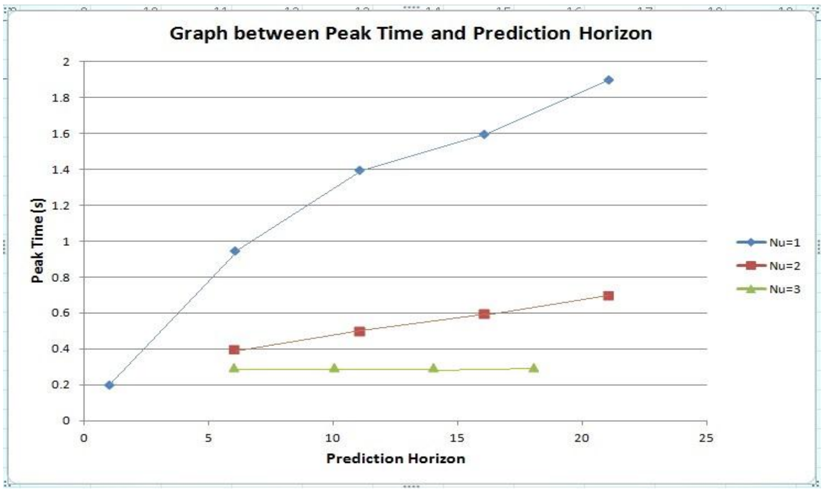

Fig. 43: Effect of Peak time w.r.t. prediction horizon

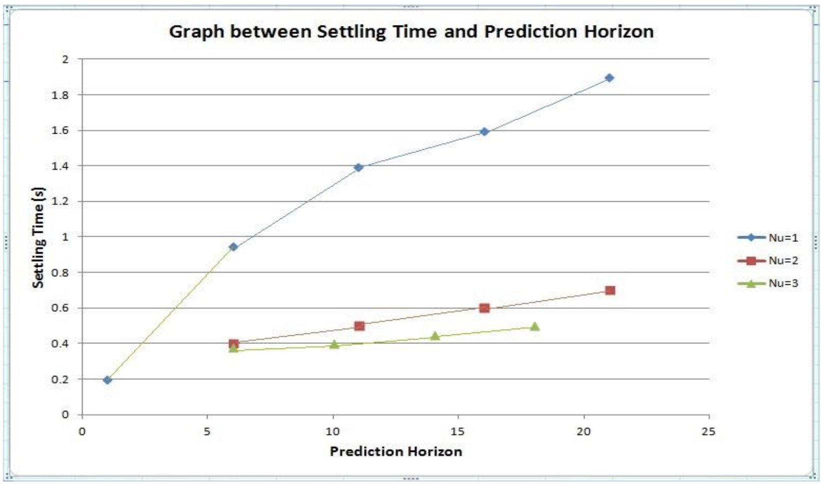

Fig. 44: Effect of Settling time w.r.t. prediction horizon

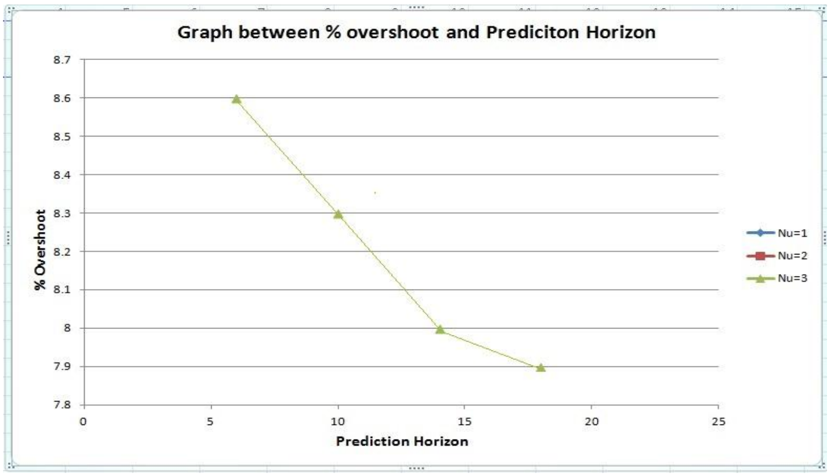

Fig. 45: Effect of Percentage overshoot w.r.t. prediction horizon

6.2 Conclusions

1. For every time constant, Rise time, Peak time and Settling time increases with increase in prediction horizon value [8]
2. Percentage overshoots decrease with increase in prediction horizon for every time constant. For m=2, no overshoots occur which shows the best suitable value to obtain effective responses [8].
3. It is found that taking smaller prediction horizon comes about the set point accomplished in much short time interval. However smaller value is more delicate to the disturbances in the model and adaptive to external disturbances [6].
4. Still this cannot be assured as the system is also affected from external disturbances such as fluid viscosity, valve positioning, parallax error, etc., so care should be taken.

6.3 Results

Different optimal values of control horizon and prediction horizon were taken by using Trial and Error method for each time constant. The graph between control and prediction horizon with respect to time constant (τ_p) is plotted and the generalized quadratic equation is obtained in terms of time constant.

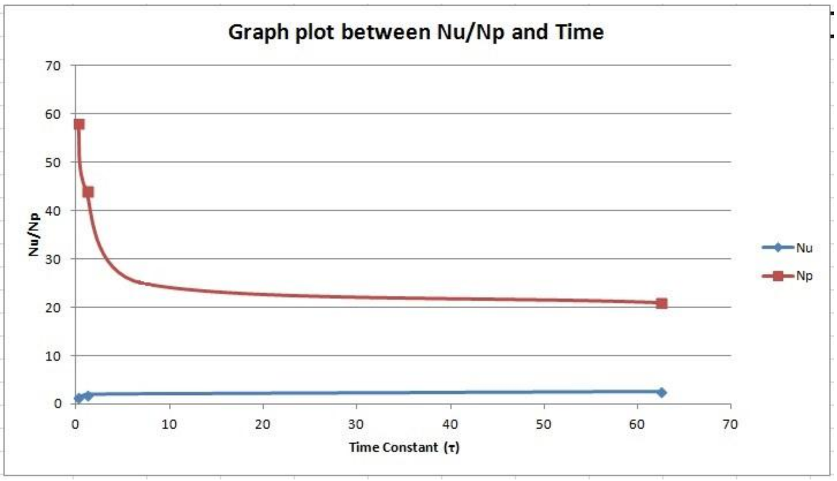

Fig. 46: Curve plot for derivation of empirical formulae

The quadratic equation obtained from the above graph gives the values of m and p for different processes which is given as

$$N_p = 0.0632\tau_p^2 - 4.5035\tau_p + 59.412$$
$$N_u = -0.0006\tau_p^2 - 0.0506\tau_p + 1.6996$$

Thus to have a stable and proper output m and p are calculated from the above given equation for different time constant for different processes [8].

6.4 Real-time application verification

For verification of the generalized empirical formulae, a real-time application is taken which is a control liquid tank. Full specification of the liquid tank system is given in Annexure 2. This is AISB – Coupled Tank Control Apparatus CTS-001. This equipment is jointly designed with Kent Bridge Instrument (Singapore) Pvt. Ltd.

The transfer function obtained from the data sheet of the brochure is given

$$C(s) = \frac{0.036}{36.942\, s^2 + 12.156\, s + 0.451}$$

This has the time constant of 7.3 seconds. For the MATLAB simulation the calculated values of m and p are 2 and 26 respectively.

With these values following response is obtained which shows that the output is stable for the defined model length.

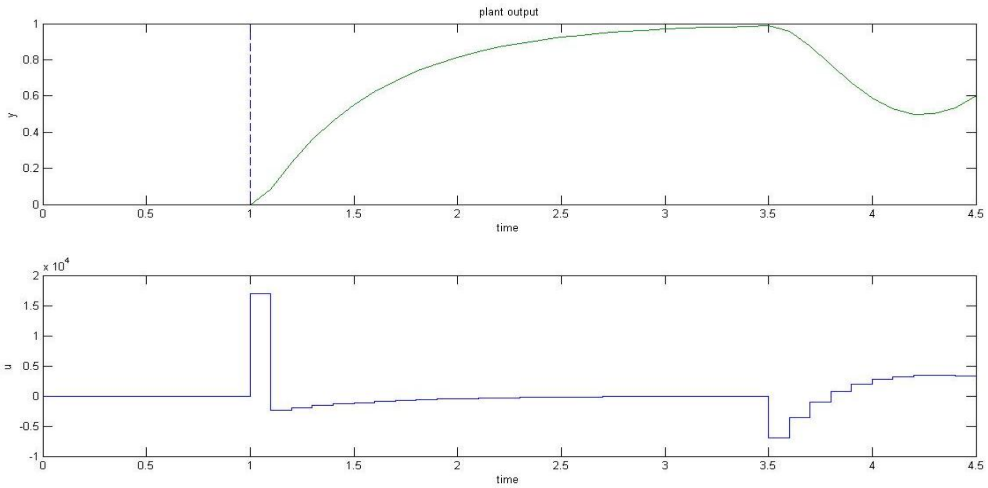

Fig. 47 Verification plot showing stable response

Following results are obtained

- Rise time = 1.8 s
- Peak time = 2.5 s
- Settling time = 2.5 s
- % Overshoot = 0 %
- Manipulated variable (u) = $1.65*10^4$
- Simulation time = 3.5 s
- Set point change time = 1 s

Chapter – 7
Conclusions

CONCLUSIONS

7.1 Conclusion

The conduct of procedure is concentrated on utilizing Dynamic Matrix Control under MATLAB window, which is in view of step response and a specific control horizon which is acquired to improve reaction of the process plant. Distinctive tuning parameters were utilized to acquire the results and their behaviour is also studied. Linearity is also discussed in brief. For Control Horizon (m) of 2, we didn't see any overshoots and the system is stable more than a characterized model length. It is figured out that taking a smaller prediction horizon (p) comes about the set point accomplished in much smaller time. Possibility and steadiness is guaranteed even for short prediction horizon which ensure that the output coming to set point. However a smaller prediction horizon is more delicate to the vulnerabilities in the model. This results in a model error and poor execution.

7.2 Future Work

Because of time restriction, some interesting jobs which are still uncovered to be done on this project. Specifically, testing the controller on the real plant process located on field areas and investigates the behavior of the process under the influence of noise and external and internal disturbances. Also computational time can be decreased to greater extent. Different types of Cost Functions can likewise be connected to decrease the time while keeping up better accuracy and performance.

REFERENCES

1. H. Pan, H. Wong, V. Kapila and M. S. Queiroz, “Experimental validation of a nonlinear backstepping liquid level controller for a state coupled two tank system,” Control Engineering Practice 13, Elsevier,2005, pp. 27–40

2. B. Wayne Bequette, Process Control: Modeling, Design and Simulation, Pearson Education Inc., USA, 2003

3. K. H. Johansson, “The Quadruple Tank Process – A Multivariable Laboratory Process with an Adjustable Zero,” IEEE Transactions on Control Systems Technology, vol. 8, no. 3, May 2000

4. S. Bhanot, “Process Control, Principle and Applications,” Oxford University Press

5. S. N. Maiti and D. N. Saraf, “ Adaptive Dynamic Matrix Control of a Distillation Column with closed loop online identification,” J. Proc. Cont., Elsevier, vol. 5, no. 5, pp. 315-327, 1995

6. J. M. Lopez, G. B. Fernandez, M. Graña, F. Oterino, “On the Influence of the Prediction Horizon in Dynamic Matrix Control,” International Journal of Control Science and Engineering, vol. 3(1): 22-30 , 2013

7. P. Tatjewski, “Advanced Control of Industrial Processes: Structures and Algorithms,” Springer Publisher, 2007

8. PUBLICATION: U. Wamhne, T. K. Dan, “Formulation of Tuning Parameters of Dynamic Matrix Control System used in a Two Tank System based on empirical relationship,” International Conference on Signal Processing, Computing and Control (2015 ISPCC), J.U.I.T., India (under review).

9. http://mathworks.org

10. http://en.wikipedia.org

Annexure 1

MATLAB Coding used for Simulations [2][9]

```
%dmcsim
%MPC tuning and simulation paramaters
n=50; %model length
p=20; %prediction horizon
m=2; %control horizon
weight=0.0; %weighting factor
ysp=1; %setpoint change (from 0)
timesp=1; %time of setpoint change
delt=0.1; %sample time
tfinal=4.5; %final simulation time
noise=0; %noise added to response coefficient
%
t=0:delt:tfinal; %time vector
kfinal=length(t); %number of time intervals
ksp=fix(timesp/delt);
r=[zeros(ksp,1);ones(kfinal-ksp,1)*ysp]; %setpoint vector
for p=26
% insert continuous model here
% model (continuos state space form)
a=[0 1;-0.0187 -0.275]; %a matrix
b=[0;0.000974]; %b matrix
c=[1 0]; %c matrix
d=[0]; %d matrix
sysc_mod=ss(a,b,c,d); %create LTI "object"
%insert plant here
%perfect model assumption (plant=model)
ap=a;
bp=b;
cp=c;
dp=d;
sysc_plant= ss(ap,bp,cp,dp);
%discretize the plant with a sample time, delt
sysd_plant= c2d(sysc_plant,delt)
[phi,gamma,cd,dd]=ssdata(sysd_plant)
%evauate discrete model step response coefficients
[s]=step(sysc_mod,[delt:delt:n*delt]);
%generate dynamic matrices(both past and future)
[Sf,Sp,Kmat] = smatgen(s,p,m,n,weight);
%plant intial conditions
xinit=zeros(size(a,1),1);
uinit=0;
yinit=0;
%initilize input vector
u =ones(min(p,kfinal),1)*uinit;
```

```
%
dup=zeros(n-2,1);
sn=s(n);
x(:,1)=xinit;
y(1)=yinit;
dist(1)=0;
% set-up is done, start simulations
for k=1:kfinal;
    %
    du(k)=dmccalc(Sp,Kmat,sn,dup,dist(k),r(k),u,k,n);
    %perform control calculation
    if k>1;
        u(k)=u(k-1)+du(k); %control input
    else
        u(k)=uinit+du(k);
    end
    %plant equations
    x(:,k+1)=phi*x(:,k)+gamma*u(k);
    y(k+1)=cd*x(:,k+1);
    %model prediction
    if k-n+1>0;
        ymod(k+1)=s(1)*du(k)+Sp(1,:)*dup+sn*u(k-n+1);
    else
        ymod(k+1)=s(1)*du(k)+Sp(1,:)*dup;
    end
    %disturbance compensation
    dist(k+1)=y(k+1)-ymod(k+1);
    %additive disturbance assumption
    %put input change into vector of past control, moves
    dup=[du(k);dup(1:n-3)];
end
%stairs plotting for input (zero-order hold) and setpoint
[tt,uu]=stairs(t,u);
[ttr,rr]=stairs(t,r);
%
figure(1)
subplot(2,1,1)
plot(ttr,rr,'--',t,y(1:length(t)))
hold on
end
ylabel('y')
xlabel('time')
title('plant output')
subplot(2,1,2)
plot(tt,uu)
ylabel('u')
xlabel('time')
```

FUNCTION FOR smatgen(s,p,m,n,weight):

```
function[Sf,Sp,Kmat] = smatgen(s,p,m,n,w)
%m= control horizon
%p= prediction horizon
%find dynamic matrix
for j=1:m;
    Sf(:,j)=[zeros(j-1,1);s(1:p-j+1)];
end
%find the matrix for past moves
for i=1:p;
    Sp(i,:)=[s(i+1:n-1)' zeros(1,i-1)];
end
%find the feedback gain matrix, Kmat
Kmat=inv(Sf'*Sf+w*eye(m))*Sf';
```

FUNCTION FOR dmccalc(Sp,Kmat,sn,dup,dist(k),r(k),u,k,n):

```
function[delu]=dmccalc(Sp,Kmat,sn,delup,d,r,u,k,n)
%calculate the optimum control move
%calculate uold=u(k-n+1)...u(k-n+p)
[m,p]=size(Kmat);
uold=zeros(p,1);
for i=1:p;
    if k-n+i>0;
        uold(i)=u(k-n+i);
    else
        uold(i)=0;
    end
end
dvec=d*ones(p,1);
rvec=r*ones(p,1);
y_free=Sp*delup+sn*uold+dvec;
e_free=rvec-y_free;
delu=Kmat(1,:)*e_free;
```

Annexure 2

Full Specifications of ASIB-Coupled Tank Control System

The AISB Coupled-Tank Control System CTS-001 is an innovative pilot plant designed for teaching both introductory and advanced control systems theory in the laboratory. This equipment is jointly designed with Kent Ridge Instrument (Singapore) Pvt. Ltd and has a world worldwide market.

Technical Specifications

- Control inputs
  Number of motor inputs: 2

- Motor voltages :0 to 5Vdc (analog) or PWM (digital)

- Power supply
  Voltage: 220-250Vac @ 50Hz

- Operating conditions
  Normal: 15-25oC @ 45-90% RH
  Max. Limit: 5-30oC @ 30-90% RH
  Transportation & storage limit: 0-70oC @ 10-95% RH

- Measurements
  Number of level measurements: 2
  Water level: 0 to 5V or 0 to 30cm (visual)

- Dimensions
  Size: 500mmLx500mmWx600mmH
  Weight: 15kg (approx.)